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Review

# Possible Application of Ecological Momentary Assessment to Older Adults' Daily Depressive Mood: Integrative Literature Review

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## Abstract

**Background:** Ecological momentary assessment is a method of investigating individuals' real-time experiences, behaviors, and moods in their natural environment over time. Despite its general usability and clinical value for evaluating daily depressive mood, there are several methodological challenges when applying ecological momentary assessment to older adults.

**Objective:** The aims of this integrative literature review were to examine possible uses of the ecological momentary assessment methodology with older adults and to suggest strategies to increase the feasibility of its application in geriatric depression research and practice.

**Methods:** We searched 4 electronic databases (MEDLINE, CINAHL, PsycINFO, and EMBASE) and gray literature; we also hand searched the retrieved articles' references. We limited all database searches to articles published in peer-reviewed journals from 2009 to 2019. Search terms were "ecological momentary assessment," "smartphone assessment," "real time assessment," "electronic daily diary," "mHealth momentary assessment," "mobile-based app," and "experience sampling method," combined with the relevant terms of depression. We included any studies that enrolled older adults even as a subgroup and that reported depressive mood at least once a day for more than 2 days.

**Results:** Of the 38 studies that met the inclusion criteria, only 1 study enrolled adults aged 65 years or older as the entire sample; the remainder of the reviewed studies used mixed samples of both younger and older adults. Most of the analyzed studies (18/38, 47%) were quantitative, exploratory (descriptive, correlational, and predictive), and cohort in design. Ecological momentary assessment was used to describe the fluctuating pattern of participants' depressive moods primarily and to examine the correlation between mood patterns and other health outcomes as a concurrent symptom. We found 3 key methodological issues: (1) heterogeneity in study design and protocol, (2) issues with definitions of dropout and adherence, and (3) variation in how depressive symptoms were measured with ecological momentary assessment. Some studies (8/38, 21%) examined the age difference of participants with respect to dropout or poor compliance rate. Detailed participant burden was reported, such as technical problems, aging-related health problems, or discomfort while using the device.

**Conclusions:** Ecological momentary assessment has been used for comprehensive assessment of multiple mental health indicators in relation to depressive mood. Our findings provide methodological considerations for further studies that may be implemented using ecological momentary assessment to assess daily depressive mood in older adults. Conducting more feasibility studies focusing on older adults with standardized data collection protocols and mixed-methods research is required to reflect users' experiences. Further telepsychiatric evaluation and diagnosis based on ecological momentary assessment data should involve standardized and sophisticated strategies to maximize the potential of ecological momentary assessment for older adults with depression in the community setting.

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**KEYWORDS**

ecological momentary assessment; depression; aged; review

# *Introduction*

## Background

It is challenging to screen for and diagnose geriatric depression due to the atypical presentations of symptoms in older populations [1]. Consequently, geriatric depression often remains unrecognized in home care settings, even when the individual receives continuous home care service [2]. If health care providers use only instrument-based interviewing to screen for depression, they detect as few as one-third of depressed older adults [2]. It is important to diversify the available and implemented assessment methods to improve detection; thus, ecological momentary assessment (EMA) may help detect depressive mood more accurately.

EMA is a method of investigating individuals' real-time experiences as they occur in their natural environment and situations over time [3]. EMA has a range of methodological strengths: (1) the "ecological" aspect represents real-world environments, allowing for increasing generalization with ecological validity; (2) the "momentary" aspect focuses on an individual's current state, which may decrease retrospective bias and errors; and (3) the "assessment" aspect provides multiple data collection points over time and across situations [3,4].

EMA methods are used in psychological research [3]. Studies have used EMA methods to investigate individual affect [5-8], behavioral problems [9], and daily mental health symptoms [5,6,10]. For depression research, EMA has much to offer in terms of improving researchers' understanding of depression because of advantages such as minimizing recall bias and detecting fluctuation of mood for a longer time [3,8]. Traditionally, researchers have relied on participants' retrospective reports about their depressive mood; however, such recall data are subject to the vagaries of cognitive heuristics and the retrieval processes [3,8]. With EMA, participants may report their mood repeatedly over time, within a familiar real-life environment, rather than reporting recollections or being interviewed in a research or laboratory setting. Researchers or clinicians can gather more ecologically valid data, which reflect participants' lifestyles or daily needs [3,8]. Thus, EMA can be used for diagnosing geriatric depression even without the screen instruments [11].

There are ongoing efforts to assure the validity, feasibility, and usability of EMA in individuals who report depressive symptoms [5,6]. For example, Hung et al [5] examined the validity and feasibility of smartphone-based EMA for Chinese patients with depression. Vachon et al [7] investigated changes in the psychological state of outpatients with major depressive disorder. Moore et al [12] found compatible psychometrics between traditional pen-and-paper and smartphone versions of EMA in emotionally distressed older adults. Among the growing body of EMA research in this area, many studies involved mixed age groups, such as middle-aged or older adults with younger participants [6,7,9,10,13-33]. Thus, it is unclear how older adults' characteristics were reflected during data collection and interpretation using EMA because older adults with mental health problems frequently have decreased self-confidence and less motivation to use new technology [34].

## Objective

Very few studies have examined the feasibility of using EMA with older adults with depressive mood [34-36]. Thus, we believe that possible implications can be extracted from studies including older adults even when they are only part of the study population. Our integrative review aimed to (1) synthesize the current information regarding the possible application of EMA to older adults' depression and (2) discuss the conceptual and methodological issues of EMA when considering further implementations in geriatric depression research and practice.

# *Methods*

This integrative review was based on a comprehensive literature search [37] and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines [38].

## Search Strategy

For this integrative literature review, we conducted a literature search from June to July 2019. Based on the initial search, only 1 study [34] met the criterion that only older adults, aged 65 years or older, were enrolled. Thus, we decided to include studies that sampled adults aged 65 years or older as part of their samples; that is, both younger and older individuals might be included in the studies. We searched 4 electronic databases: MEDLINE (through PubMed), CINAHL, PsycINFO, and EMBASE. We searched the gray literature, including dissertations, conference proceedings (papers or abstracts), and editorials, in the Virginia Henderson International Nursing Library and CINAHL (exclusively focusing on gray literature). We performed an additional manual search using the Google Scholar online tool, based on an ancestry search of citation and reference lists obtained from articles we retrieved from the targeted databases.

The initial sets of search terms consisted of "ecological momentary assessment," "smartphone assessment," "real time assessment," "electronic daily diary," "mHealth momentary assessment," "mobile-based app," or "experience sampling method," combined with "affect," "mood," and "emotion," as well as "depress*" to reflect different relevant terms such as depression, depressed, or depressive (Multimedia Appendix 1).

### *Inclusion Criteria*

Inclusion criteria were as follows: (1) studies enrolled at least some participants aged 65 years or older; (2) study participants reported EMA in the community setting; (3) studies measured momentary affect, such as depressive symptoms, depressed mood, negative affect, or negative emotion at least once a day for more than 2 days; (4) studies used certain types of instruments or devices to report participants' momentary mood or scores, either electronic devices (eg, smartphone, personal digital assistant, or palm computer) or traditional pen-and-paper recording tools; (5) studies were published in English; and (6) studies were published between 2009 and 2019.

### *Exclusion Criteria*

Exclusion criteria were as follows: (1) participants' ages were not clearly reported or were determined to be less than 64 years using the available information regarding the study sample's means, ranges, and proportion of age groups; (2) studies included a negligible proportion of older adults (eg, 65-69 years old) within a wide range of participant ages; (3) studies measured momentary affect such as depressive symptoms, depressed mood, negative affect, or negative emotion using non-EMA tools; and (4) studies were methodological studies comparing the reliability between traditional and electronic measurements of EMA. If an article was a systematic review, Cochrane review, literature review, case study, or expert opinion, we used it as background information and examined the references to expand our manual literature search; however, we did not include such reviews in the analysis.

### Data Extraction, Analysis, and Synthesis

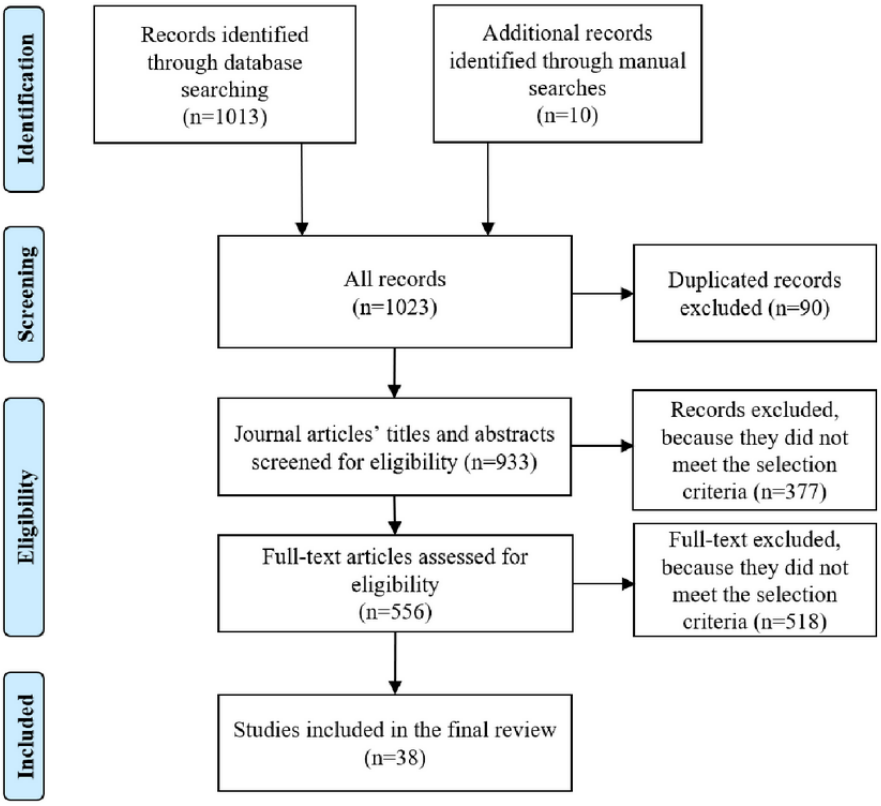
Four authors (YRJ, HYK, NHK, and HJK) initially screened titles and abstracts based on eligibility criteria and reviewed the full text of articles. These researchers had an acceptable level of agreement of over 95% regarding final selection of the articles. Four authors (YRJ, HYK, NHK, and HJK) extracted the data from the selected articles into an analysis table. Two authors (SK and SSK) validated and confirmed the analyzed data between articles and table entries for accuracy (99% verification).

## Results

### Characteristics of Selected Studies and Participants

The searches retrieved 1013 records from the 4 databases and gray literature, and 10 records from the manual search. After screening the results against our eligibility criteria, we selected 38 studies for review that met our inclusion criteria (Figure 1). Multimedia Appendix 2 summarizes the characteristics of the 38 selected studies and their participants.

**Figure 1.** Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram outlining the search and review process.



### *Study Aims and Design*

All 38 studies applied a longitudinal design to observe depressive mood throughout EMA from several days to months to emphasize the benefit of multiple-timescale aspects of the study design. Most of the analyzed studies (18/38, 47%) were quantitative, exploratory (descriptive, correlational, and predictive), and cohort in design [6,9,10,15,18-20,22,24,25,28,32,33,36,39-42]. Approximately half of the studies used EMA primarily to assess depressive mood over time. However, the other half of the studies used EMA to examine other symptoms or health problems and collected information on depressive mood as concurrent or associated factors. Frequent aims of these studies were to (1) describe the fluctuating pattern of participants' depressive mood and relevant characteristics and (2) identify concurrent and lagged association of the depressive mood with other psychological factors. Few studies examined predisposing situations and conditions that might influence a lagged effect of depressive mood. Other types of study designs were used to achieve different purposes. Two methodological studies [7,23] aimed to determine the validity, reliability, and user evaluation of EMA over time. Two studies applied a mixed-methods research approach [34,43] to assess perceived acceptability, adherence rates, and reasons for poor compliance or nonadherence to smartphone-based EMA in older adults or to examine participants' qualitative responses.

### *Study Participants*

Only 1 study enrolled adults aged 65 years or older as the entire sample [34]. The remainder of the reviewed studies used mixed samples of both younger and older adults, with ages ranging from 18 to 97 years. Some studies involved advanced age groups, such as middle-aged or older adults, with younger participants [6,7,9,10,13-33]. The sample size of surveyed studies ranged from 12 to 404, which varied according to study purpose, data collection method, and analysis plans. Some studies specifically aimed to enroll study participants with depressive mood and relevant mental health problems (7/38, 18%) [7,9,13,17,23,24,34], other physical health problems or diseases (8/38, 21%) [6,29,31,36,40,43-45], or chronic pain (2/38, 5%) [16,25], which may be related to depressive mood. Some studies aimed to enroll study participants who had an alcohol or smoking habit (4/38, 11%) [22,28,33,46] or obesity (2/38, 5%) [19,20]. However, several studies (15/38, 40%) did not specify any particular disease or condition [10,14,15,18,21,26,27,30,32,39,41,42,47-49].

## Measures of Depression and Other Variables

Multimedia Appendix 2 and Multimedia Appendix 3 summarize the characteristics of EMA measurements used in the 38 selected studies.

### *Measures of Baseline Depression and Concurrent Characteristics*

Most studies (22/38, 58%) examined depressive mood at baseline using a diverse array of clinically valid screening instruments or established diagnostic criteria. Several screening or diagnostic instruments were used: the Mini International Neuropsychiatric Interview [13,22,50]; Hamilton Rating Scale for Depression [13,29,51]; Beck Depression Inventory [7,13,48,52,53]; Patient Health Questionnaire (PHQ) [39,54]; Composite International Diagnostic Interview [40,55]; Montgomery-Asberg Depression Rating Scale [9,56]; *Diagnostic and Statistical Manual of Mental Disorders* (Fourth Edition) (DSM-IV) [7,17,23,34,57,58]; Structured Clinical Interview for the DSM-IV-Text Revision [10,25,59]; Patient-Reported Outcomes Measurement Information System (PROMIS) [34,60]; Center for Epidemiologic Studies Depression Scale (CES-D) [15,30,36,47,61]; Positive and Negative Affect Schedule (PANAS) [49,62]; Positive and Negative Syndrome Scale [24,63]; Hospital Anxiety and Depression Scale [16,43,64,65]; and Hamilton Depression Inventory [31,66]. The researchers of each study used this information to describe sample characteristics at baseline or included the data as a controlled variable in their analyses.

Some relevant characteristics were also examined along with depressive mood. Most studies included variables relating to momentary experiences, activities, or behaviors occurring before or at the time of report [6,9,13,16,17,21,23-32,39-44,47,48]. Some studies also included concurrent symptoms of depression such as fatigue [6,29,36,42,45], pain [6,16,25,31,36,40,43,45,48,49], stress [9,10,18-22,26,28,29,32,33,41,42,44,46], anxiety [7,9,10,13,14,16,17,21,24-26,34,39-43,45,47], loneliness [14,20,23,24,27,31,42,46,47], or cognitive impairment [7,14,22,27,34].

### *Measures of Momentary Depressive Mood*

When employing EMA, most studies did not clearly define "momentary mood of depression," and there was no consistency of operational definition across the 38 selected studies. Moreover, the depressive score was defined in diverse terms, such as depressive or negative mood and affect [6,7,9,10,13-29,31-34,36,39-48], sadness [9,15,17-22,24-30,32,33,36,39,42,44,46,48,49], feeling down [13,14,23,47], or relevant symptoms of depression [6,29,31,34,45]. In some studies, depression was included as a set of subitems of global affect or mood [7,9,10,13,16,21,26,36,39-44], whereas other studies treated depressive scores separately from other measurements that might have been taken [6,30,31,34,45].

A single item was usually used to measure momentary depression in most studies (35/38, 92%), whereas only a few studies employed multiple items to assess symptoms of depression [31,34,36]. Most reporting mechanisms relied on a Likert scale (30/38, 79%), visual analog scale (6/38, 16%), or sliding bar scale (2/38, 5%) in the form of points or a sliding bar. Some of the surveyed studies (14/38, 37%) clearly stated that the question used to measure depression was extracted from widely used instruments, such as the PANAS [10,14,20,39,44,62], PANAS-Expanded Form [15,67], circumplex model of emotion [17,68], circumplex model of affect [19,26,69], PROMIS [34,70], Philadelphia Geriatric Center Positive and Negative Affect Rating Scale [36,71], CES-D-Revised [7,72], DSM-IV [29,57], or PHQ [31,54]. Those instruments were different from the measures used at baseline to screen participants' depression diagnosis or initial status.

A range of different EMA devices were used to record momentary data. Of the 38 studies, 17 (45%) used computerized handheld devices [6,7,15,17,18,24,25,28,29,32,33,41,42,44,45,47,49], whereas 14 studies (14/38, 37%) used smartphone or web-based EMA apps, or both [9,14,16,19-21,23,26,30,34,39,40,43,46]. One study (1/38, 3%) employed telephone-based EMA via phone interview [36], and another relied on an automatic cell phone call [31]. One study (1/38, 3%) made a direct call and entered scores with an input keypad [22]. A few studies (3/38, 8%) used pen-and-paper–based EMA or booklets using a timekeeping mechanism [13,27,48]. One study (1/38, 3%) asked participants to record a diary via email, but their device was unclear [10].

Observation times varied widely across the studies. The number of repeated EMA measurements ranged from 1 to 10 per day, from 5 to 180 days. Thus, the total number of repeated EMA measurements ranged from 14 to 360. Several studies divided the EMA measurement period into 2 or more periods spaced over several months [18,20,21,23,26,30,34,47]; however, the other studies conducted EMA measurements within a consecutive period of days.

Most studies (36/38, 95%) provided detailed information about how EMA was applied within specific timing, except for 2 studies [30,43]. In several studies, participants received automatic notifications at fixed times [7,10,16,17,25,32,39,42,44,46]. In other studies, the participant received an automatic notice at random within the researcher- or participant-designated time interval in a day [6,9,13,14,21-23,29,36,40,41,48]. Other studies used a totally randomized time frame in a day [24,26,27,34,47,49]. Several studies used mixed methods, employing fixed or random and individualized time based on sleep and daily activities [15,18-20,28,31,33,45].

## Feasibility: Dropout, Adherence, and Subjective Evaluation

Many studies (34/38, 90%) defined dropout, compliance, adherence, or active usage. Multimedia Appendix 4 summarizes each concept's definition and reported rate.

### Definition and Overall Rate

Many studies defined dropout as participants who exhibited noncompliance during the study period [7,10,15,16,29,43]. One study applied liberal criteria by excluding those who never used EMA [10], whereas other researchers were relatively conservative, excluding even those who partially participated in the EMA but did not strictly follow the reporting protocols [7,15,29]. In addition, 11 studies (11/38, 29%) did not provide a clear operational definition of dropout, although they reported the rate of dropout. Based on these variously defined criteria and unclear information available across studies, the dropout rate among studies varied significantly, from 1.3% [10] to 25.9% [14].

Studies also reported mixed definitions of adherence and compliance. In 3 studies [7,9,45], these were defined as the degree of completion, calculated by dividing the number of completed ratings by the potential maximum number of required EMA observations. Other studies applied a specific required completion rate to classify whether a given participant adhered to or complied with EMA, such as 30% [34], 50% [6], or 100% [34]. Due to the inconsistency of adherence criteria, large variations in adherence rates were observed starting from 65.1% [9]. A total of 8 studies (8/38, 21%) examined age difference of dropout or poor compliance rate, but they reported that advanced age was not associated with different compliance or satisfaction with EMA reports [16,17,21,26,32,43,48,49]. However, 1 study [46] reported that older drinkers were more compliant than the younger group, specifically in the evening survey than in the morning ones.

### Subjective Evaluation

Few studies reported specific reasons for participant dropout or lack of compliance when assessing EMA use. Those studies that did report this information noted that the most common reasons for withdrawing from study participation were loss of contact, acute health problems, adverse personal events, and decreasing interest or inability to complete the protocol [7,30]. Ramsey et al [34] reported detailed information regarding nonadherence specifically in older adults. The common themes of nonadherence were classified as (1) a technical problem or user error; (2) logistical mismatch with competing demands in the participant's daily life; (3) health-related barriers, such as sensory, cognitive, or functional impairment; and (4) discomfort involved with carrying the device or completing EMA.

There was some researcher support to assure feasibility. For example, a previous study developed a mobile app that could run on both Android and iOS, allowing each study participant to choose the operating system with which he or she was most comfortable [5]. Because the app did not require an internet connection to record the score [5], study participants could log EMA reports anytime and anywhere. Alarming using a beeping prompt is very helpful to remind study participants of timely reports [13,24,25,27,33,42,44,48]. Specifically considering older adult participants' potential sensory impairments, Ravesloot et al [6] provided additional assistance, such as a larger-format device or magnifiers for those with visual impairments and a stylus for those with dexterity problems.

# Discussion

## Principal Findings

This integrative review of the literature on EMA implementation in research provides some understanding of whether and how EMA may be feasibly applied with older adults when reporting daily depression or relevant conditions. Diverse conceptual and methodological issues should be considered when developing EMA protocols, and researchers should strive to establish rigorous validation procedures and clinical applications targeting older adults.

### Heterogeneity in Study Design and Protocol

EMA protocols are more complicated and time consuming than traditional one-time surveys. The 38 studies reviewed used a great diversity of protocols, with little consistency in the methodologies. Some studies used new protocols developed by the researchers [29] or previously established ones from large-scale studies [9]. Protocol content encompassed optimal frequency, duration, and interval of data collection, as well as the device employed to collect the data. Based on the technology acceptance model framework [73], EMA systems should be very simple, reducing users' cognitive errors and enhancing response accuracy. Thus, single items were most frequently used for EMA as longitudinally intensive designs because repeated use of multi-item scales may be impractical for a depressed sample [74], specifically older adults. However, a single question has lower construct validity than multiple questions. Thus, researchers should make a careful decision when choosing fewer items from preexisting measures to assess geriatric depression.

To assure ecological validity, most studies adopted an individualized protocol, which increased the heterogeneity of the studies. EMA reporting time within a day should consider each individual's lifestyle, preference, and convenience [7,75] to minimize interrupting participants' daily lives [7,9], such as sleep [9]. It is important to collect information on participants' current engagement in daily life activities, location, and social context or event when engaging in EMA [6,9,30,31,39,44]. This information could be used to differentiate normal patterns in a participant's daily life versus abnormal data that occur in specific situations or environments [34].

Diverse theories were used in the EMA studies identified in our review [14,22,25,26,30,32,44], such as the social support theoretical model [44]; the Intraindividual Study of Affect, Health, and Interpersonal Behavior [30]; the strength and vulnerability integration theory [32]; the communal coping model [25]; the social action theory [22] and the dynamic model of relapse [22]; and the cognitive appraisal theory [14]; as well as a mix of hedonic motivation [26] and operant conditioning [26]. It is important to conceptualize complex psychosocial processes measured by multiple-time assessment and modeling. Any theory employed to underpin research in this area should be modified appropriately, focusing on psychological aspects of specific age groups to promote clinical practice emphasizing socioenvironmental factors. This theoretical effort may promote the context-sensitive development of appropriate study protocols, taking into account individual and population needs.

### *Issues With Definitions of Dropout and Adherence*

Some degree of dropout and nonadherence occurred with wide variability. Common reasons for dropout or lack of adherence were associated with technical, logistical, physical, and cognitive problems, similar to issues reported in previous studies [34,76], rather than with advanced age. Thus, the selected studies carefully screened participants who might be lacking in technological aptitude based on medical and functional conditions that could inhibit accurate EMA reporting rather than excluding participants based solely on advanced age [9,10,16,18,22,25,29,32,34,36,40,45-47]. Some studies excluded individuals from participation when they had (1) severe cognitive impairment, such as dementia; (2) severe symptoms of cognitive or emotional disturbances; or (3) other psychiatric diagnoses (eg, schizophrenia or substance abuse) requiring intensive treatment and hospitalization. EMA studies with depressed older adults should be preceded by comprehensive assessment, including physical examination, cognitive and functional tests, and an intensive personal interview regarding health conditions. In addition, it is important to ensure ease, comfort, satisfaction, and accessibility when using an EMA device, app, or system [6]. Familiarity may be increased by developing a user-friendly app's features, visual layout, or system based on users' experience [5].

### *Variation in How Depressive Symptoms Were Measured With EMA Devices*

EMA was applied to measure daily depressive mood using electronic devices such as smart devices, computerized handheld devices, or telephones. Most studies used an electronic diary format rather than personal direct interviewing [36], aligning with the dramatic development of information and communication technology in the field. Because EMA requires multiple self-reporting instances in daily life, electronic and smart devices may be more suitable for this type of research; they are portable and easy to use in a range of situations and at various times [7].

However, device training should be provided to participants, particularly in light of diverse participant backgrounds and technological experience [77]. Although none of the 38 selected studies reported details about the training procedure itself, the participants were instructed on how to respond to prompts regarding their psychological state of momentary mood [6,7,13,15,17-20,23-26,28-34,40-42,45,47-49]. Researchers usually checked participants' understanding of EMA report, functions of the device, or early compliance through daily review [9,17,22,28,31-34,44,49]. After that, some researchers provided the participants with a device practice opportunity under a researcher's supervision [31,32,34] or rental of the device [6,20,23,24,28,29,33,40,46,49]. Several studies provided a training guidebook [6,20,25,40,49]. To apply EMA in practice, it is important that health care professionals learn how to use information and communication technology devices on their own, then teach the techniques to their patients or patients' families to monitor older adults' symptoms [78].

## Implications for Research and Practice

Based on our study findings, EMA could enhance health care professionals' ability to detect changes in patient-reported emotions (eg, mindfulness, depression, and anxiety) in comparison with standard assessment instruments [12]. However, more research should be conducted with older adult participants to confirm the technique's suitability in this context. It may be difficult to generalize our review findings due to mixed samples of diverse age groups. However, the identified methodological challenges should be overcome by further studies in both clinical and community settings. Specifically, future research should investigate factors that influence adherence and complete use of EMA when this technique is used as a self-monitoring system reflecting clinical and ecological validation along with the value of technology.

Health care professionals should prepare themselves to use EMA by engaging in multimodal training prior to performing their role; moreover, they should deliver timely device training adapted to meet the needs of diverse study participants [79]. Health care providers typically learn via hands-on experience based on a trial-and-error system or postprofessional certification programs [80]. To enhance standardization and rigor, as well as to improve implementation, health care professionals should be made aware of the importance of EMA, as well as the methodological challenges of appropriately implementing EMA when dealing with geriatric depression. Our study findings could be fundamental to developing user-centered EMA strategies for older users.

## Limitations

This study had several limitations. First, we initially attempted to include only adults aged 65 years or older; however, only 1 study met this criterion [34]. Thus, this integrative literature review included studies that accepted participants aged 18 years or older, including older adults. This limitation precluded our study findings to apply directly to older adults only. Our study findings may be appropriate for studies including both younger and older adults by using methodological approaches that specifically accommodate or are tailored to older adults. In the future, EMA research specifically targeting older adults needs to be conducted, and further analysis is required. Second, due to limited age-related information in the surveyed studies, we were unable to perform quantitative examinations to assess how proportions of older adults relate to adherence or dropout rates.

## Conclusions

EMA is becoming an increasingly popular approach to assess depressive symptoms, and this technique has particular clinical value with older adults. This integrative literature review provides a distinctive understanding of the feasibility of employing EMA to investigate depressive mood among older adults. In the studies under review, EMA was used to examine the correlation between pattern of mood and other health outcomes and to investigate changes in this pattern caused by triggers in terms of effects on treatment and reported symptoms. Further research and guidelines for clinical practice should be developed in consideration of how to evaluate participants' competence to complete EMA; how to prevent dropout, nonadherence, and data incompleteness; how to use valid measures of momentary depressive mood; how to standardize EMA protocols; and how to ensure sufficient sample sizes. Our study findings support the need to overcome these methodological challenges and facilitate future research demonstrating the clinical implications of EMA, and suggest the next step toward the successful development of ecological momentary interventions for older adults with depression.

## Acknowledgments

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## Conflicts of Interest

None declared.

Multimedia Appendix 1
Search strategy overview.
[DOCX File , 15 KB - mental_v7i6e13247_app1.docx ]

Multimedia Appendix 2
Characteristics of the 38 selected studies.
[DOCX File , 48 KB - mental_v7i6e13247_app2.docx ]

Multimedia Appendix 3
Summary of the characteristics of ecological momentary assessment used in the 38 studies.
[DOCX File , 55 KB - mental_v7i6e13247_app3.docx ]

Multimedia Appendix 4
Definitions and rates of dropout, adherence, and compliance used in the selected studies.
[DOCX File , 35 KB - mental_v7i6e13247_app4.docx ]

## References

1. Vieira ER, Brown E, Raue P. Depression in older adults: screening and referral. J Geriatr Phys Ther 2014;37(1):24-30. [doi: 10.1519/JPT.0b013e31828df26f] [Medline: 23619921]
2. Brown EL, Bruce ML, McAvay GJ, Raue PJ, Lachs MS, Nassisi P. Recognition of late-life depression in home care: accuracy of the outcome and assessment information set. J Am Geriatr Soc 2004 Jun;52(6):995-999. [doi: 10.1111/j.1532-5415.2004.52271.x] [Medline: 15161468]

3. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. Annu Rev Clin Psychol 2008 Apr;4:1-32. [doi: 10.1146/annurev.clinpsy.3.022806.091415] [Medline: 18509902]
4. Stone AA, Shiffman S. Ecological momentary assessment (EMA) in behavioral medicine. Ann Behav Med 1994 Sep;16(3):199-202. [doi: 10.1093/abm/16.3.199]
5. Hung S, Li MS, Chen YL, Chiang JH, Chen YY, Hung GC. Smartphone-based ecological momentary assessment for Chinese patients with depression: an exploratory study in Taiwan. Asian J Psychiatr 2016 Oct;23:131-136. [doi: 10.1016/j.ajp.2016.08.003] [Medline: 27969071]
6. Ravesloot C, Ward B, Hargrove T, Wong J, Livingston N, Torma L, et al. Why stay home? Temporal association of pain, fatigue and depression with being at home. Disabil Health J 2016 Apr;9(2):218-225. [doi: 10.1016/j.dhjo.2015.10.010] [Medline: 26750976]
7. Vachon H, Bourbousson M, Deschamps T, Doron J, Bulteau S, Sauvaget A, et al. Repeated self-evaluations may involve familiarization: an exploratory study related to ecological momentary assessment designs in patients with major depressive disorder. Psychiatry Res 2016 Nov;245:99-104. [doi: 10.1016/j.psychres.2016.08.034] [Medline: 27541343]
8. Wenze SJ, Miller IW. Use of ecological momentary assessment in mood disorders research. Clin Psychol Rev 2010 Aug;30(6):794-804. [doi: 10.1016/j.cpr.2010.06.007] [Medline: 20619520]
9. Depp CA, Moore RC, Dev SI, Mausbach BT, Eyler LT, Granholm EL. The temporal course and clinical correlates of subjective impulsivity in bipolar disorder as revealed through ecological momentary assessment. J Affect Disord 2016 Mar;193:145-150 [FREE Full text] [doi: 10.1016/j.jad.2015.12.016] [Medline: 26773907]
10. Eldahan AI, Pachankis JE, Jonathon Rendina H, Ventuneac A, Grov C, Parsons JT. Daily minority stress and affect among gay and bisexual men: a 30-day diary study. J Affect Disord 2016 Jan;190:828-835 [FREE Full text] [doi: 10.1016/j.jad.2015.10.066] [Medline: 26625095]
11. Kim H, Lee S, Lee S, Hong S, Kang H, Kim N. Depression prediction by using ecological momentary assessment, Actiwatch data, and machine learning: observational study on older adults living alone. JMIR Mhealth Uhealth 2019 Oct;7(10):e14149 [FREE Full text] [doi: 10.2196/14149] [Medline: 31621642]
12. Moore RC, Depp CA, Wetherell JL, Lenze EJ. Ecological momentary assessment versus standard assessment instruments for measuring mindfulness, depressed mood, and anxiety among older adults. J Psychiatr Res 2016 Apr;75:116-123 [FREE Full text] [doi: 10.1016/j.jpsychires.2016.01.011] [Medline: 26851494]
13. Crowe E, Daly M, Delaney L, Carroll S, Malone KM. The intra-day dynamics of affect, self-esteem, tiredness, and suicidality in major depression. Psychiatry Res 2019 Sep;279:98-108. [doi: 10.1016/j.psychres.2018.02.032] [Medline: 29661498]
14. de Hoog N, Verboon P. Is the news making us unhappy? The influence of daily news exposure on emotional states. Br J Psychol 2019 Mar:1-17 [FREE Full text] [doi: 10.1111/bjop.12389] [Medline: 30900253]
15. Mogle J, Muñoz E, Hill NL, Smyth JM, Sliwinski MJ. Daily memory lapses in adults: characterization and influence on affect. J Gerontol B Psychol Sci Soc Sci 2019 Jan;74(1):59-68 [FREE Full text] [doi: 10.1093/geronb/gbx012] [Medline: 28329832]
16. Jamison RN, Mei A, Ross EL. Longitudinal trial of a smartphone pain application for chronic pain patients: predictors of compliance and satisfaction. J Telemed Telecare 2018 Feb;24(2):93-100. [doi: 10.1177/1357633X16679049] [Medline: 27831496]
17. Lamers F, Swendsen J, Cui L, Husky M, Johns J, Zipunnikov V, et al. Mood reactivity and affective dynamics in mood and anxiety disorders. J Abnorm Psychol 2018 Oct;127(7):659-669. [doi: 10.1037/abn0000378] [Medline: 30335438]
18. Neubauer AB, Smyth JM, Sliwinski MJ. When you see it coming: stressor anticipation modulates stress effects on negative affect. Emotion 2018 Apr;18(3):342-354. [doi: 10.1037/emo0000381] [Medline: 29154583]
19. Elliston KG, Ferguson SG, Schüz N, Schüz B. Situational cues and momentary food environment predict everyday eating behavior in adults with overweight and obesity. Health Psychol 2017 Apr;36(4):337-345. [doi: 10.1037/hea0000439] [Medline: 27669177]
20. Forman EM, Schumacher LM, Crosby R, Manasse SM, Goldstein SP, Butryn ML, et al. Ecological momentary assessment of dietary lapses across behavioral weight loss treatment: characteristics, predictors, and relationships with weight change. Ann Behav Med 2017 Oct;51(5):741-753. [doi: 10.1007/s12160-017-9897-x] [Medline: 28281136]
21. Liao Y, Solomon O, Dunton GF. Does the company of a dog influence affective response to exercise? Using ecological momentary assessment to study dog-accompanied physical activity. Am J Health Promot 2017 Sep;31(5):388-390. [doi: 10.1177/0890117116666947] [Medline: 27609907]
22. Maisto SA, Xie FC, Witkiewitz K, Ewart CK, Connors GJ, Zhu H, et al. How chronic self-regulatory stress, poor anger regulation, and momentary affect undermine treatment for alcohol use disorder: integrating social action theory with the dynamic model of relapse. J Soc Clin Psychol 2017 Mar;36(3):238-263. [doi: 10.1521/jscp.2017.36.3.238]
23. Verhagen SJW, Berben JA, Leue C, Marsman A, Delespaul PAEG, van Os J, et al. Demonstrating the reliability of transdiagnostic mHealth Routine Outcome Monitoring in mental health services using experience sampling technology. PLoS One 2017 Oct;12(10):e0186294 [FREE Full text] [doi: 10.1371/journal.pone.0186294] [Medline: 29023568]
24. Vasconcelos e Sa D, Wearden A, Hartley S, Emsley R, Barrowclough C. Expressed emotion and behaviourally controlling interactions in the daily life of dyads experiencing psychosis. Psychiatry Res 2016 Nov;245:406-413. [doi: 10.1016/j.psychres.2016.08.060] [Medline: 27611070]

25. Burns JW, Gerhart JI, Post KM, Smith DA, Porter LS, Schuster E, et al. The communal coping model of pain catastrophizing in daily life: a within-couples daily diary study. J Pain 2015 Nov;16(11):1163-1175 [FREE Full text] [doi: 10.1016/j.jpain.2015.08.005] [Medline: 26320945]
26. Dunton GF, Liao Y, Intille S, Huh J, Leventhal A. Momentary assessment of contextual influences on affective response during physical activity. Health Psychol 2015 Dec;34(12):1145-1153. [doi: 10.1037/hea0000223] [Medline: 26053885]
27. Floridou GA, Müllensiefen D. Environmental and mental conditions predicting the experience of involuntary musical imagery: an experience sampling method study. Conscious Cogn 2015 May;33:472-486. [doi: 10.1016/j.concog.2015.02.012] [Medline: 25800098]
28. Epler AJ, Tomko RL, Piasecki TM, Wood PK, Sher KJ, Shiffman S, et al. Does hangover influence the time to next drink? An investigation using ecological momentary assessment. Alcohol Clin Exp Res 2014 May;38(5):1461-1469 [FREE Full text] [doi: 10.1111/acer.12386] [Medline: 24588377]
29. Mazure CM, Weinberger AH, Pittman B, Sibon I, Swendsen J. Gender and stress in predicting depressive symptoms following stroke. Cerebrovasc Dis 2014;38(4):240-246 [FREE Full text] [doi: 10.1159/000365838] [Medline: 25401293]
30. Ram N, Conroy DE, Pincus AL, Lorek A, Rebar A, Roche MJ, et al. Examining the interplay of processes across multiple time-scales: illustration with the Intraindividual Study of Affect, Health, and Interpersonal Behavior (iSAHIB). Res Hum Dev 2014;11(2):142-160 [FREE Full text] [doi: 10.1080/15427609.2014.906739] [Medline: 26989350]
31. Wolf LD, Davis MC. Loneliness, daily pain, and perceptions of interpersonal events in adults with fibromyalgia. Health Psychol 2014 Sep;33(9):929-937 [FREE Full text] [doi: 10.1037/hea0000059] [Medline: 25180546]
32. Scott SB, Sliwinski MJ, Blanchard-Fields F. Age differences in emotional responses to daily stress: the role of timing, severity, and global perceived stress. Psychol Aging 2013 Dec;28(4):1076-1087 [FREE Full text] [doi: 10.1037/a0034000] [Medline: 24364410]
33. Piasecki TM, Jahng S, Wood PK, Robertson BM, Epler AJ, Cronk NJ, et al. The subjective effects of alcohol-tobacco co-use: an ecological momentary assessment investigation. J Abnorm Psychol 2011 Aug;120(3):557-571 [FREE Full text] [doi: 10.1037/a0023033] [Medline: 21443289]
34. Ramsey AT, Wetherell JL, Depp C, Dixon D, Lenze E. Feasibility and acceptability of smartphone assessment in older adults with cognitive and emotional difficulties. J Technol Hum Serv 2016;34(2):209-223 [FREE Full text] [doi: 10.1080/15228835.2016.1170649] [Medline: 27683018]
35. Rullier L, Atzeni T, Husky M, Bouisson J, Dartigues JF, Swendsen J, et al. Daily life functioning of community-dwelling elderly couples: an investigation of the feasibility and validity of ecological momentary assessment. Int J Methods Psychiatr Res 2014 Jun;23(2):208-216 [FREE Full text] [doi: 10.1002/mpr.1425] [Medline: 24375556]
36. Smith DM, Parmelee PA. Within-day variability of fatigue and pain among African Americans and non-Hispanic whites with osteoarthritis of the knee. Arthritis Care Res (Hoboken) 2016 Jan;68(1):115-122 [FREE Full text] [doi: 10.1002/acr.22690] [Medline: 26315851]
37. Conn VS, Isaramalai SA, Rath S, Jantarakupt P, Wadhawan R, Dash Y. Beyond MEDLINE for literature searches. J Nurs Scholarsh 2003;35(2):177-182. [doi: 10.1111/j.1547-5069.2003.00177.x] [Medline: 12854300]
38. Moher D, Liberati A, Tetzlaff J, Altman DG, PRISMA Group. Preferred Reporting Items for Systematic Reviews and Meta-Analyses: the PRISMA statement. PLoS Med 2009 Jul;6(7):e1000097 [FREE Full text] [doi: 10.1371/journal.pmed.1000097] [Medline: 19621072]
39. Hooker SA, Masters KS. Daily meaning salience and physical activity in previously inactive exercise initiates. Health Psychol 2018 Apr;37(4):344-354. [doi: 10.1037/hea0000599] [Medline: 29369678]
40. Paolillo EW, Obermeit LC, Tang B, Depp CA, Vaida F, Moore DJ, et al. Smartphone-based ecological momentary assessment (EMA) of alcohol and cannabis use in older adults with and without HIV infection. Addict Behav 2018 Aug;83:102-108 [FREE Full text] [doi: 10.1016/j.addbeh.2017.10.016] [Medline: 29126667]
41. Poulin MJ, Brown SL, Ubel PA, Smith DM, Jankovic A, Langa KM. Does a helping hand mean a heavy heart? Helping behavior and well-being among spouse caregivers. Psychol Aging 2010 Mar;25(1):108-117 [FREE Full text] [doi: 10.1037/a0018064] [Medline: 20230132]
42. Dunton GF, Atienza AA, Castro CM, King AC. Using ecological momentary assessment to examine antecedents and correlates of physical activity bouts in adults age 50+ years: a pilot study. Ann Behav Med 2009 Dec;38(3):249-255 [FREE Full text] [doi: 10.1007/s12160-009-9141-4] [Medline: 20052568]
43. Jamison RN, Mei A, Edwards RR, Ross EL. Efficacy of vibrating gloves for chronic hand pain due to osteoarthritis. Pain Med 2018 May;19(5):1044-1057. [doi: 10.1093/pm/pnx230] [Medline: 29025096]
44. Paterson C, Jones M, Rattray J, Lauder W, Nabi G. What is the mechanism effect that links social support to coping and psychological outcome within individuals affected by prostate cancer? Real time data collection using mobile technology. Eur J Oncol Nurs 2016 Apr;21:126-133. [doi: 10.1016/j.ejon.2015.09.002] [Medline: 26440544]
45. Hachizuka M, Yoshiuchi K, Yamamoto Y, Iwase S, Nakagawa K, Kawagoe K, et al. Development of a personal digital assistant (PDA) system to collect symptom information from home hospice patients. J Palliat Med 2010 Jun;13(6):647-651. [doi: 10.1089/jpm.2009.0350] [Medline: 20509795]

46. Kuerbis A, Treloar Padovano H, Shao S, Houser J, Muench FJ, Morgenstern J. Comparing daily drivers of problem drinking among older and younger adults: an electronic daily diary study using smartphones. Drug Alcohol Depend 2018 Feb;183:240-246 [FREE Full text] [doi: 10.1016/j.drugalcdep.2017.11.012] [Medline: 29306171]
47. van Knippenberg RJM, de Vugt ME, Ponds RW, Myin-Germeys I, Verhey FRJ. An experience sampling method intervention for dementia caregivers: results of a randomized controlled trial. Am J Geriatr Psychiatry 2018 Dec;26(12):1231-1243. [doi: 10.1016/j.jagp.2018.06.004] [Medline: 30126766]
48. Droit-Volet S, Wearden JH. Experience sampling methodology reveals similarities in the experience of passage of time in young and elderly adults. Acta Psychol (Amst) 2015 Mar;156:77-82. [doi: 10.1016/j.actpsy.2015.01.006] [Medline: 25701720]
49. Kööts L, Realo A, Allik J. The influence of the weather on affective experience: an experience sampling study. J Individ Differ 2011;32(2):74-84. [doi: 10.1027/1614-0001/a000037]
50. Sheehan DV, Lecrubier Y, Sheehan KH, Amorim P, Janavs J, Weiller E, et al. The Mini-International Neuropsychiatric Interview (M.I.N.I.): the development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. J Clin Psychiatry 1998;59(Suppl 20):22-33;quiz 34-57. [Medline: 9881538]
51. Hamilton M. A rating scale for depression. J Neurol Neurosurg Psychiatry 1960 Feb;23(1):56-62 [FREE Full text] [doi: 10.1136/jnnp.23.1.56] [Medline: 14399272]
52. Beck AT, Steer RA, Brown GK. BDI-II, Beck Depression Inventory: Manual. 2nd edition. San Antonio, TX: Psychology Corporation; 1996.
53. Beck AT, Ward CH, Mendelson M, Mock J, Erbaugh J. An inventory for measuring depression. Arch Gen Psychiatry 1961 Jun;4(6):561-571. [doi: 10.1001/archpsyc.1961.01710120031004] [Medline: 13688369]
54. Kroenke K, Spitzer RL. The PHQ-9: a new depression and diagnostic severity measure. Psychiatr Ann 2002 Sep;32(9):509-515. [doi: 10.3928/0048-5713-20020901-06]
55. World Health Organization. Composite International Diagnostic Interview (CIDI, version 2.1). Geneva, Switzerland: World Health Organization; 1997.
56. Montgomery SA, Asberg M. A new depression scale designed to be sensitive to change. Br J Psychiatry 1979 Apr;134(4):382-389. [Medline: 444788]
57. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders, 4th Edition, Text Revision (DSM-IV-TR). Washington, DC: American Psychiatric Association Press; 2000.
58. First MB, Spitzer RL, Gibbon M, Williams JBW. Structured Clinical Interview for DSM-IV Axis I Disorders (SCID-I). Washington, DC: American Psychiatric Publishing; 1997.
59. First MB, Spitzer RL, Gibbon M, Williams JBW. Structured Clinical Interview for DSM-IV-TR Axis I Disorders, Research Version, Patient Edition with Psychotic Screen (SCID-I/P W/ PSY SCREEN). New York, NY: Biometrics Research Department, Columbia University; 2002.
60. Gershon RC, Cella D, Fox NA, Havlik RJ, Hendrie HC, Wagster MV. Assessment of neurological and behavioural function: the NIH Toolbox. Lancet Neurol 2010 Mar;9(2):138-139. [doi: 10.1016/S1474-4422(09)70335-7] [Medline: 20129161]
61. Radloff LS. The CES-D scale: a self-report depression scale for research in the general population. Appl Psychol Meas 1977 Jun;1(3):385-401. [doi: 10.1177/014662167700100306]
62. Watson D, Clark LA, Tellegen A. Development and validation of brief measures of positive and negative affect: the PANAS scales. J Pers Soc Psychol 1988 Jun;54(6):1063-1070. [Medline: 3397865]
63. Kay SR, Fiszbein A, Opler LA. The Positive and Negative Syndrome Scale (PANSS) for schizophrenia. Schizophr Bull 1987;13(2):261-276 [FREE Full text] [Medline: 3616518]
64. Zigmond AS, Snaith RP. The Hospital Anxiety and Depression Scale. Acta Psychiatr Scand 1983 Jun;67(6):361-370. [Medline: 6880820]
65. Bjelland I, Dahl AA, Haug TT, Neckelmann D. The validity of the Hospital Anxiety and Depression Scale: an updated literature review. J Psychosom Res 2002 Feb;52(2):69-77. [doi: 10.1016/s0022-3999(01)00296-3] [Medline: 11832252]
66. Reynolds WM, Kobak KA. Hamilton Depression Inventory: A Self-report Version of the Hamilton Depression Rating Scale (HDRS). Odessa, FL: Psychological Assessment Resources, Inc; 1995.
67. Watson D, Clark LA. The PANAS-X: Manual for the Positive and Negative Affect Schedule-Expanded Form. Iowa City, IA: The University of Iowa; 1994.
68. Larsen RJ, Diener E. Promises and problems with the circumplex model of emotion. In: Clark MS, editor. Review of Personality and Social Psychology, No. 13. Emotion. Thousand Oaks, CA: Sage Publications, Inc; 1992:25-59.
69. Russell JA. A circumplex model of affect. J Pers Soc Psychol 1980;39(6):1161-1178. [doi: 10.1037/h0077714]
70. Cella D, Yount S, Rothrock N, Gershon R, Cook K, Reeve B, PROMIS Cooperative Group. The Patient-Reported Outcomes Measurement Information System (PROMIS): progress of an NIH Roadmap cooperative group during its first two years. Med Care 2007 May;45(5 Suppl 1):S3-S11 [FREE Full text] [doi: 10.1097/01.mlr.0000258615.42478.55] [Medline: 17443116]
71. Lawton MP, Parmelee PA, Katz IR, Nesselroade J. Affective states in normal and depressed older people. J Gerontol B Psychol Sci Soc Sci 1996 Nov;51(6):309-316. [doi: 10.1093/geronb/51b.6.p309] [Medline: 8931618]

72. Eaton WW, Muntaner C, Smith C, Tien A, Ybarra M. Center for epidemiologic studies depression scale: review and revision (CESD and CESD-R). In: Maruish ME, editor. The Use of Psychological Testing for Treatment Planning and Outcomes Assessment. 3rd edition. Mahwah, NJ: Lawrence Erlbaum; 2004:363-377.
73. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 1989 Sep;13(3):319-340. [doi: 10.2307/249008]
74. Ebner-Priemer UW, Trull TJ. Ecological momentary assessment of mood disorders and mood dysregulation. Psychol Assess 2009 Dec;21(4):463-475. [doi: 10.1037/a0017075] [Medline: 19947781]
75. Hershenberg R, Mavandadi S, Wright E, Thase ME. Anhedonia in the daily lives of depressed veterans: a pilot report on experiential avoidance as a moderator of emotional reactivity. J Affect Disord 2017 Jan;208:414-417. [doi: 10.1016/j.jad.2016.10.011] [Medline: 27814567]
76. Fritz H, Tarraf W, Saleh DJ, Cutchin MP. Using a smartphone-based ecological momentary assessment protocol with community dwelling older African Americans. J Gerontol B Psychol Sci Soc Sci 2017 Sep;72(5):876-887 [FREE Full text] [doi: 10.1093/geronb/gbw166] [Medline: 28057696]
77. Kim H, Park E, Lee S, Kim M, Park EJ, Hong S. Self-management of chronic diseases among older Korean adults: an mHealth training, protocol, and feasibility study. JMIR Mhealth Uhealth 2018 Jun;6(6):e147 [FREE Full text] [doi: 10.2196/mhealth.9988] [Medline: 29959109]
78. Smedley A. The importance of informatics competencies in nursing: an Australian perspective. Comput Inform Nurs 2005;23(2):106-110. [doi: 10.1097/00024665-200503000-00011] [Medline: 15772512]
79. Rutledge CM, Kott K, Schweickert PA, Poston R, Fowler C, Haney TS. Telehealth and eHealth in nurse practitioner training: current perspectives. Adv Med Educ Pract 2017;8:399-409 [FREE Full text] [doi: 10.2147/AMEP.S116071] [Medline: 28721113]
80. Papanagnou D, Sicks S, Hollander JE. Training the next generation of care providers: focus on telehealth. Healthc Transform 2015 Dec;1(1):52-63. [doi: 10.1089/heat.2015.29001-psh]

## Abbreviations

**CES-D:** Center for Epidemiologic Studies Depression Scale
**DSM-IV:** Diagnostic and Statistical Manual of Mental Disorders (Fourth Edition)
**EMA:** ecological momentary assessment
**PANAS:** Positive and Negative Affect Schedule
**PHQ:** Patient Health Questionnaire
**PROMIS:** Patient-Reported Outcomes Measurement Information System

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Original Paper

# Causal Factors of Anxiety and Depression in College Students: Longitudinal Ecological Momentary Assessment and Causal Analysis Using Peter and Clark Momentary Conditional Independence

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## Abstract

**Background:** Across college campuses, the prevalence of clinically relevant depression or anxiety is affecting more than 27% of the college population at some point between entry to college and graduation. Stress and self-esteem have both been hypothesized to contribute to depression and anxiety levels. Although contemporaneous relationships between these variables have been well-defined, the causal relationship between these mental health factors is not well understood, as frequent sampling can be invasive, and many of the current causal techniques are not well suited to investigate correlated variables.

**Objective:** This study aims to characterize the causal and contemporaneous networks between these critical mental health factors in a cohort of first-year college students and then determine if observed results replicate in a second, distinct cohort.

**Methods:** Ecological momentary assessments of depression, anxiety, stress, and self-esteem were obtained weekly from two cohorts of first-year college students for 40 weeks (1 academic year). We used the Peter and Clark Momentary Conditional Independence algorithm to identify the contemporaneous (t) and causal (t-1) network structures between these mental health metrics.

**Results:** All reported results are significant at $P<.001$ unless otherwise stated. Depression was causally influenced by self-esteem ($t$-1 $r_p$, cohort 1 [C1]=–0.082, cohort 2 [C2]=–0.095) and itself ($t$-1 $r_p$, C1=0.388, C2=0.382) in both cohorts. Anxiety was causally influenced by stress ($t$-1 $r_p$, C1=0.095, C2=0.104), self-esteem ($t$-1 $r_p$, C1=–0.067, C2=–0.064, $P$=.002), and itself ($t$-1 $r_p$, of C1=0.293, C2=0.339) in both cohorts. A causal link between anxiety and depression was observed in the first cohort ($t$-1 $r_p$, C1=0.109) and only observed in the second cohort with a more liberal threshold ($t$-1 $r_p$, C2=0.044, $P$=.03). Self-esteem was only causally influenced by itself ($t$-1 $r_p$, C1=0.389, C2=0.393). Stress was only causally influenced by itself ($t$-1 $r_p$, C1=0.248, C2=0.273). Anxiety had positive contemporaneous links to depression ($t$ $r_p$, C1=0.462, C2=0.444) and stress ($t$ $r_p$, C1=0.354, C2=0.358). Self-esteem had negative contemporaneous links to each of the other three mental health metrics, with the strongest negative relationship being stress ($t$ $r_p$, C1=–0.334, C2=–0.340), followed by depression ($t$ $r_p$, C1=–0.302, C2=–0.274) and anxiety ($t$ $r_p$, C1=–0.256, C2=–0.208). Depression had positive contemporaneous links to anxiety (previously mentioned) and stress ($t$ $r_p$, C1=0.250, C2=0.231).

**Conclusions:** This paper is an initial attempt to describe the contemporaneous and causal relationships among these four mental health metrics in college students. We replicated previous research identifying concurrent relationships between these variables and extended them by identifying causal links among these metrics. These results provide support for the vulnerability model of depression and anxiety. Understanding how causal factors impact the evolution of these mental states over time may provide key information for targeted treatment or, perhaps more importantly, preventative interventions for individuals at risk for depression and anxiety.

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**KEYWORDS**

depression; anxiety; self-esteem; stress; causality; ecological momentary assessments; mental health; network; college

# Introduction

## Depression and Anxiety Prevalence and Risk Factors

Worldwide, depression is estimated to affect over 300 million individuals, and anxiety is estimated to affect over 260 million individuals [1]. A recent survey in the United States showed that individuals 18-25 years of age had the highest rate of major depressive episodes with a prevalence of over 13% [2]. On college campuses across the United States, more than 66% of students reported overwhelming anxiety within the last 12 months and more than 46% reported being so depressed it was difficult to function [3]. In the same report, more than 27% of undergraduates were found to have been diagnosed or treated for anxiety, depression, or both. In this paper, we focus on first-year undergraduate students, as they are a high-risk demographic going through a variety of life changes, many of which are risk factors for depression and anxiety, including living in a new geographic location, attending a new school, and meeting new friends [4-6]. This complex and changing period in students' lives provides a unique window into the complex relationship between mental health metrics.

Two factors that may precipitate anxious or depressive symptoms are increased stress and low self-esteem [4,7-10]. Because stress and low self-esteem are often correlated with anxiety and depression, it can be difficult to disentangle the causal associations between these factors. New methodological developments in causal network reconstruction permits the estimation of causal networks from time series data. Implementing these methods might allow for the estimation of the causal network relating stress, self-esteem, anxiety, and depression among college students. If increased stress and low self-esteem are causal markers that precede anxiety and depression, then these methods might be useful for earlier identification or preventative intervention for people at risk. Moreover, they may help to identify factors that could be targets for programmatic or institutional changes and, thereby, reduce the prevalence of anxiety and depression.

## Defining Mental Health Metrics for Ultrabrief Measurements

Identifying temporal patterns of occurrence and causal factors underlying these mental disorders will be critical to addressing the growing mental health problems on college campuses and elsewhere. An unresolved question is the exact nature of causal relationships between the four variables previously mentioned. Although multiple definitions exist for these constructs, we focus on a subset of these, so they can be surveyed frequently and with minimal effort needed by the subject. Stress can be defined as a negative emotional or physical experience that has subsequent physiological or behavioral changes directed toward adaptation, either by changing the situation or accommodating its effects [11]. In this study, we focus on self-reported stress, given the complexities associated with measuring actual stress exposure. State self-esteem is considered a person's sense of their own worth or value at the current moment [12]. The Patient Health Questionnaire (PHQ)-4 is frequently used as a brief measure with relatively good diagnostic performance for depression and anxiety, being comprised of the PHQ-2 and Generalized Anxiety Disorder-2 (GAD-2) [13]. As measured within this context, anxiety will be considered persistent and excessive worry. Similarly, depression is multifaceted, but we will focus on anhedonia and negative affect components, given their gross diagnostic abilities of anxiety and depression in college students [14]. Although focusing on these specific aspects of these mental health metrics is likely to be limiting, they allow for quick and more frequent assessments while maintaining rough diagnostic abilities.

## Models of Depression and Anxiety

There are a variety of models that predict how these variables influence each other across the lifespan. Data supporting these models have generally been sparsely sampled, with weeks or months separating 3-5 waves (time points) for each survey [15,16]. Here we focus on a few of these models, giving precedence to models with strong empirical support where primary relationships between two or more variables are mentioned. The vulnerability model of mental health [17] suggests that vulnerability and the likelihood of a mental health episode are linked in a trait-state relationship. Recent adaptations of the vulnerability model specifically predict that low self-esteem will lead to subsequent increases in depression and have received strong empirical support [18]. The diathesis-stress model postulates that there is a wide constellation of factors that may predispose someone to depression or anxiety and that stress is a moderating variable. Many models of anxiety are also based on the vulnerability model. These models include a stressor or trigger that may lead to subsequent increases in anxious symptoms and progress to clinical levels of anxiety, depending on the context [19,20]. The scar model predicts that depressive periods may lead to future low self-esteem [21,22]. The reciprocal relation model posits that stress leads to future anxiety and anxiety leads to future stress, and low self-esteem leads to increased depression and depression leads to future low self-esteem [18]. These diverse and not always complementary models beg testing with many time points, which may be able to more fully elucidate the relationship between true causal relationships. At a time where replication in social and affective neuroscience is in question, it is critically important to replicate results in distinct cohorts when possible [23,24].

### Ecological Momentary Assessments to Measure Mental Health Metrics

Increasing the sampling rate and study duration compared to previous causal studies would provide unique insight into the relationships among these mental health metrics. Recent technological advances allow for more frequent sampling with ecological momentary assessments (EMAs), which can be less invasive and more naturalistic than typical laboratory-based studies if the sampling frequency is not burdensome. With EMAs, questions can be sent directly to a person's smartphone as often as desired [25,26]. EMA frequency should be balanced to minimize demand on the subject while maximizing coverage of potentially rapidly changing responses related to underlying mental health metrics with consideration for subject retention over the entire study duration. In an attempt to retain individuals across their entire collegiate experience, we selected weekly EMA sampling.

### Causal and Contemporaneous Network Detection

The ability to sample individuals' mental health metrics more frequently allows for the possibility of testing models and theories present in the psychological literature, as well as generating new ones. With larger amounts of data, more methods to analyze causal influences can be considered. Autoregressive models such as Granger causality can be used to assess aspects of causation in an observed system [27]. Notably, Granger causality is susceptible to high dimensionality and missing data, and most implementations are not able to dissociate causal influences from highly correlated variables in a reasonable manner. Given the correlation present between the measured mental health metrics, Granger causality is not a reasonable method to select. Luckily, recent advances in causal network detection methods allow for parsing large, correlated time series with missing data. Peter and Clark Momentary Conditional Independence (PCMCI) is a method that can reconstruct robust causal networks for time series data that contain some missing points (ie, nonresponses from students in this study) while dealing with high dimensionality and highly correlated variables more effectively than many other methods while still retaining a low false-positive rate [28,29].

Although many research groups have demonstrated that stress, self-esteem, anxiety, and depression are all correlated, an unresolved question is if there are causal influences between these variables. A variety of psychological models related to interactions of these mental health metrics have been proposed, but much of the extant literature does not have temporal frequency and the total number of time points required to perform many of the recently developed causality methods. In this study, we aim to characterize the causal network of relationships between stress, self-esteem, depression, and anxiety as assessed by EMAs collected through the smartphone app, StudentLife. We first test this in a sample of first-year college students using PCMCI, then retest the same analysis in a completely independent cohort of subjects. Subsequently, we attempt to determine which psychological models of anxiety and depression best fit the current results and discuss possible implications.

## Methods

### Participants

Participants were first-year undergraduate students with eligible smartphones recruited from the Dartmouth College community during their first academic term. The Committee for the Protection of Human Subjects at Dartmouth College approved this study. Each participant provided written informed consent in accordance with guidelines set by the committee and received their choice of either course credit or monetary compensation (US $10 per week of EMAs answered) for study participation [30]. A subsample of cohort 1 (C1) participants were included in a previous study [31]. Two cohorts, corresponding to subsequent class years, were included. C1 included 106 subjects (75 females, mean age at the beginning of the study 18.25 years, SD 0.63, range 18-22). One subject was removed from the study for having a phone incompatible with our data collection app, leaving C1 with 105 subjects. Cohort 2 (C2) included 114 subjects (75 females, mean age at the beginning of the study 18.12 years, SD 0.45, range 18-20). One subject withdrew within a week of starting the study, and their data was excluded from further analyses, leaving C2 with 113 subjects.

### Ecological Momentary Assessments and Data Processing

Brief surveys of depression, anxiety, stress, and state self-esteem were assessed for 40 weeks (1 academic year) using EMAs (Multimedia Appendix 1), a method to assess an individual's mental state in a naturalistic setting outside of the laboratory [25]. StudentLife, an app for Android and iOS, was installed on each participant's smartphone [32] and used to administer EMAs at a random time point once per week for 40 weeks. Individuals were also able to manually open the StudentLife app and take the EMA in an unprompted manner. Data from StudentLife is uploaded to a secure server whenever a participant is both using WiFi and charging their phone, which they were encouraged to do daily. The EMA questions analyzed in this study included the PHQ-4, with depressive (PHQ-2) and anxious (GAD-2) components [13]. State self-esteem was measured with three questions selected from the State Self-Esteem Scale, which included a relevant question from each of the following categories: social, appearance, and performance [33]. Stress was measured by asking "Are you feeling stressed now?" with a 5-point Likert scale [34] with response labels ranging from "Not at All" to "Extremely." Anonymized data was exported from StudentLife servers. Responses for an individual were averaged in the rare case that multiple responses were received within a given week. Individuals were able to access and answer the EMAs whenever they wanted, not just when prompted by the app. Weekly responses from all subjects were concatenated and buffered with three lines of missing values so that transition points between subjects would not weigh as causal influences. All missing values were replaced with "999." C1 had 3404 weeks of responses to all four mental health metrics (mean 28.8, median 30, SE 0.74) across 105 individuals, and C2 had 3614 weeks of responses (mean 26.7, median 29, SE 0.77) across 114 individuals. A total of 7018 out of 8760 possible weeks contained responses across 219 individuals (80% response rate).

### Causal and Contemporaneous Network Detection

The goal of the current work is to determine the causal and contemporaneous network structure among the mental health metrics collected on a weekly basis. Contemporaneous network structure is the relationship between variables within the same time point, while causal network structure is the relationship between variables at different time points. PCMCI has the advantage of being able to recover causal networks that include multiple sources of causation and is suitable for data sets with missing responses and correlated variables [28,29,35]. PCMCI was implemented using the partial correlation method from the Tigramite software package (version 4.0.0) [36]. PCMCI is a two-step method that begins with a fully connected causal network graph. Condition selection, or PC1, a modification of the Peter and Clark algorithm, is the first step of PCMCI, which attempts to reduce the number of connections in the graph. Momentary conditional independence (MCI) is the second step of PCMCI, which consists of testing links for causal relationships (using partial correlations in this study).

Condition selection is a method to reduce the number of network connections that are interrogated for causal influences. Condition selection identifies nodes from previous time points that are likely to be real connections. Condition selection is the first phase of the PCMCI algorithm implemented in Tigramite [37] and is performed to reduce the number of potential causal connections interrogated. It applies a fast variant of PC1, a modification of the Peter and Clark algorithm [38] (for an in-depth description of PC1 and PCMCI please refer to [29]). PC1 identifies relevant conditions (variable at a given time lag) that may have predictive power for all variables. In this context, condition selection is performed using a liberal initial alpha value of .2 to retain more possible connections than not (as is recommended by the software author in the documentation [36] and is the default for the function in Tigramite version 4.0.0) while reducing the total number of connections to be tested in the second phase of PCMCI.

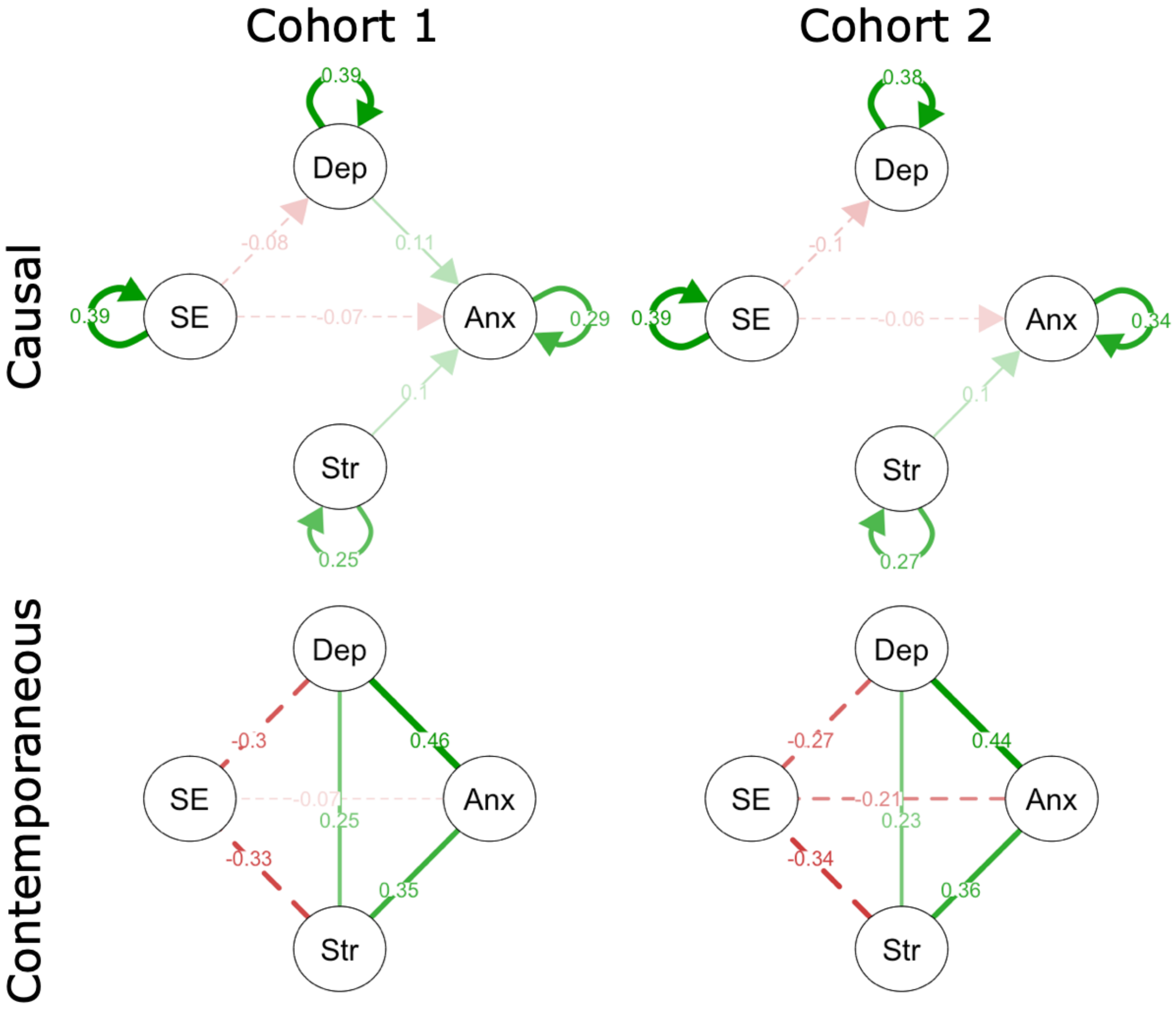
MCI, the second step of PCMCI, identifies contemporaneous and causal relationships from the reduced set of connections passed to it from the PC1 algorithm. Contemporaneous relationships are those that occur at the same time or faster than the sampling rate (within the same week in this study) and directionality cannot be assessed. Causal relationships are those that occur across time points (between weeks in this study). MCI was implemented through partial correlation estimated with a linear ordinary least squares regression and a test for nonzero linear Pearson correlation on the residuals at an alpha of .005. By using condition selection (PC1) paired with MCI using the partial correlation test, this method is able to account for autocorrelation, leading to well-controlled false-positive rates [28]. Partial correlation was selected from available test statistics within this framework due to its ease of interpretability, ability to work with all survey values, and ability to measure the association between a given pair of variables while removing variance associated with other variables, critical when looking at highly correlated mental health metrics. Visualization of contemporaneous and causal network graphs were generated using qgraph [39].

## Results

Causal influences are shown as directed lines with arrow heads revealing directionality (Figure 1, top), while contemporaneous influences are shown separately with undirected lines for clearer visualization (Figure 1, bottom). All displayed connections were significant at $P<.005$. Relationships described in the text were significant at $P<.001$ unless otherwise mentioned. Depression was causally influenced by self-esteem ($t$-1 $r_p$, C1=–0.082, C2=–0.095) and itself ($t$-1 $r_p$, C1=0.388, C2=0.382) in both cohorts. Anxiety was causally influenced by stress ($t$-1 $r_p$, C1=0.095, C2=0.104), self-esteem ($t$-1 $r_p$, C1=–0.067, C2=–0.064, $P$=.002), and itself ($t$-1 $r_p$, C1=0.293, C2=0.339) in both cohorts. A causal link between anxiety and depression was observed in the first cohort ($t$-1 $r_p$, C1=0.109) and only observed in the second cohort with a more liberal threshold ($t$-1 $r_p$, C2=0.044, $P$=.03 not displayed in Figure 1). Self-esteem was not causally influenced by any metrics except for itself ($t$-1 $r_p$, C1=0.389, C2=0.393). Stress was not causally influenced by any metrics except for itself ($t$-1 $r_p$, C1=0.248, C2=0.273).

The PCMCI partial correlation ($r_p$) analysis of contemporaneous relationships revealed significant contemporaneous influences ($P<.001$) among all four mental health metrics (Figure 1, top). Observed contemporaneous undirected links (time $t$) included positive links between anxiety, depression, and stress. Anxiety had positive contemporaneous links to depression ($t$ $r_p$, C1=0.462, C2=0.444) and stress ($t$ $r_p$, C1=0.354, C2=0.358). Self-esteem had negative contemporaneous links to each of the other three mental health metrics, with the strongest negative relationship being stress ($t$ $r_p$, C1=–0.334, C2=–0.340), followed by depression ($t$ $r_p$, C1=–0.302, C2=–0.274) and anxiety ($t$ $r_p$, C1=–0.256, C2=–0.208). Depression had positive contemporaneous links to anxiety (previously mentioned) and stress ($t$ $r_p$, C1=0.250, C2=0.231).

**Figure 1.** Causality graph observing previous week (t-1) connections on mental health metrics collected through ecological momentary assessments weekly for cohorts 1 (top left) and 2 (top right) at a threshold of *P*<.005. Contemporaneous connections presented for cohorts 1 (bottom left) and 2 (bottom right). Solid lines are positive relationships and dashed lines are negative relationships with magnitude marked on the graph, listing the partial correlation value. For causal relationships, the arrowhead signifies directionality. Anx: anxiety; Dep: depression; SE: self-esteem; Str: stress.



## Discussion

### Summary of Primary Findings

Weekly EMAs of self-esteem, depression, stress, and anxiety were collected in two separate cohorts of over 200 college students across an academic year, with an average response rate of 80%. These EMAs were submitted to the PCMCI algorithm, which identified increased stress as a causal factor of future anxiety. Decreased self-esteem was identified as a causal factor of future depression and, to a lesser extent, anxiety. Increased depression was observed as a causal factor for future anxiety, but only in one of the two cohorts at a threshold of *P*<.005. These results help confirm the vulnerability model and extend previous literature by providing evidence for model testing.

This paper and previous research show congruent patterns of correlation among the mental health metrics observed [40]: positive relationships among depression, anxiety, and stress, and inverse relationships between self-esteem and the other mental health metrics. These findings are also congruent with previously validated similarities between these EMA surveys and longer web-based surveys of related mental health metrics [31,41]. Analyses using PCMCI provide insight into the causal temporal dynamics between these mental health metrics. Positive correlations were observed among depression, anxiety, and stress, while these 3 metrics were negatively correlated with self-esteem, as expected based on previous research.

### Causal Network Detection

The most novel and important part of this study is the application of the PCMCI algorithm for the identification of the causal network structure among mental health metrics [28]. PCMCI is a two-part algorithm, which when compared to other causality-detection algorithms, provides low false-positive rates combined with high power to detect real causal links. By reducing the number of connections tested in the causal network using PC1, PCMCI allows for higher dimensional data to be tested when compared with Granger causality or most other causal methods. By using partial correlation as the testing metric for the MCI phase of PCMCI, all variables are tested simultaneously, and interactions between correlated variables can be dissociated, something that has been elusive when implementing Granger causality. Within the current data set, conditioning with PC1 is likely less important, as we are using only four variables, while using partial correlation is critically important, and these mental health metrics are all at least somewhat correlated. The current results show that increases in stress cause subsequent increases in anxiety, while increases in self-esteem cause subsequent decreases in depression and, to a lesser extent, anxiety. These findings are consistent with the extant literature [7,40], but, to our knowledge, we are the first group to run a causal network analysis with moderately dense (weekly) temporal coverage extending across a whole academic year (40 weeks), identifying similar results across two distinct cohorts.

## Causal Findings and Existing Theories of Depression and Anxiety

The causal interactions among these mental health metrics can provide evidence to support some current psychological theories. This paper supports the vulnerability model, which suggests that low self-esteem can lead to subsequent depression or anxiety (Figure 1) [42,43]. We did not observe evidence supporting the scar model, where depression causally influences self-esteem, or the reciprocal relation model, where low self-esteem and depression have a feedback loop. Other groups have observed some support for the scar model, but to a lesser extent than the vulnerability model [7,8]. The meta-analysis by Sowislo and Orth [7] looked at prospective effects between these variables for each study, many of which included longer time frames with less frequent sampling than we observed here. It is possible that we would need to greatly increase the number of time points modeled as possible causal factors and collect data for a longer period of time to observe effects in support of the scar model.

The diathesis-stress model has been applied in both depressive and anxious contexts, where pre-existing conditions such as low self-esteem are risk factors, and stressful events can trigger subsequent increases in depression or anxiety in higher risk individuals [9]. There is some support for the diathesis-stress model in this paper, where self-esteem is a causal factor for anxiety and depression, and stress is a causal factor for anxiety. Conversely, with a time lag of 1 week, we did not see direct interactions between stress and self-esteem. It is possible that the interactions hypothesized between these variables in the diathesis-stress model may play out on a much longer timescale than observed here (multiple to many months or years, which has some support in the literature) or may primarily be related to trait self-esteem and not state self-esteem as measured here.

## Future Directions and Limitations

Although the current work provides an analysis of regularly sampled mental health metrics in a college population, a lag of 1 week was selected for simplicity and interpretability. It is possible that other lag intervals may provide additional insight into the causal dynamics of these variables. Given how rapidly mental states can change, weekly resolution may not be the optimal timescale to detect causality between these variables, where more frequent sampling could help further elucidate contemporaneous changes. Moreover, longitudinal sampling over many years may be better suited to testing the scar model [44]. There are a variety of moderating factors such as gender, socioeconomic status, and first-generation college student status that could potentially alter the observed results and should be investigated in future work.

The frequency of sampling needs to be balanced with the burden on study participants, since requesting frequent responses would likely lead to increased participant attrition and may even be an added stressor. As the current study looks to retain individuals over their entire college experience, minimizing the burden on the participant is likely to be a key to retention. Given the goal of long-term participant retention, the total number of questions asked through weekly EMAs was minimized, meaning limited coverage of anxiety or depressive symptoms. Although this may restrict the overarching implications that can be drawn from the current study, the questions were selected based on previous validation and maximal ability to diagnose anxious or depressive symptoms while asking minimal questions [13,14]. Furthermore, the questions from the PHQ-4 were not changed from Kroenke and colleagues [13], meaning they asked about the last 2 weeks, which may be suboptimal for the elucidation of causal factors and likely to underestimate the true magnitude of causal influences.

Values of these mental health metrics may change more rapidly than the weekly rate that they are sampled at in this study. Signals associated with fast fluctuations in these metrics would decrease our ability to identify relationships, particularly those that replicate across multiple cohorts, suggesting that the observed results are real and, if anything, underestimate the strength of the relationship between these variables. Increasing the sampling rate to daily or hourly could provide greatly improved insights into the nature of the temporal relationships between these metrics; although, it would increase participant burden and possibly decrease retention. A balance may be provided by using mobile smartphone sensing features to provide some insight into the optimal EMA sampling frequency for future studies. Smart triggering of EMAs, which is based on changes in smartphone features such as motion, conversation, or location, could reduce the total number of times a participant is asked to answer EMA questions while optimizing the temporal resolution and helping to better determine causal relationships among variables. Smartphone sensing features can be sampled hourly or even by the minute with little participant burden except for decreased battery life. Identifying sets of features such as the number of conversations, sleep, or number of locations visited [41] that predict shifts in mental states may help with both smart triggering of EMAs and identification of a more precise moment in time when an individual's feelings change [45,46]. Identifying predictive features would add complexities to the data analysis pipeline and could be critical to balancing the amount of time requested of each participant over several years, as well as the temporal resolution needed to properly elucidate causal structures. Many theories and models have been created to describe the relationship among these mental health metrics. With increased survey sampling rates available with EMA and improvements in methods for detecting causal network structure, the ability to test these models and generate more refined ones becomes a possibility.

## Conclusions

This study provides a framework for identifying causal factors of anxiety and depression in college students, with the key results replicating in two distinct cohorts sampled weekly over the course of an academic year. Stress is a causal predictor of anxiety, while low self-esteem is a causal predictor of depression and, to a lesser extent, anxiety. These results support the vulnerability model of depression and suggest that ameliorating high rates of stress may reduce subsequent increases in self-reported anxiety. Continually testing and expanding models of the interactions between these and other mental health metrics will be critical to identifying causal factors and potential treatments or strategies to mitigate them, particularly in groups who are at a higher risk than the general population.

## Conflicts of Interest

None declared.

Multimedia Appendix 1
Ecological momentary assessments asked of participants on a weekly basis with the StudentLife app.
[DOC File , 33 KB - mental_v7i6e16684_app1.doc ]

## References

1. World Health Organization. World Mental Health Day 2017 URL: https://www.who.int/mental_health/world-mental-health-day/2017/en/
2. National Institute of Mental Health.: National Institute of Mental Health; 2019. Major depression URL: https://www.nimh.nih.gov/health/statistics/major-depression.shtml [accessed 2019-11-20]
3. American College Health Association. American College Health Association national college health assessment Spring 2006 reference group data report (abridged): the American College Health Association. J Am Coll Health 2007 Jan;55(4):195-206. [doi: 10.3200/jach.55.4.195-206]
4. Beiter R, Nash R, McCrady M, Rhoades D, Linscomb M, Clarahan M, et al. The prevalence and correlates of depression, anxiety, and stress in a sample of college students. J Affect Disord 2015 Mar 01;173:90-96. [doi: 10.1016/j.jad.2014.10.054] [Medline: 25462401]
5. Darling CA, McWey LM, Howard SN, Olmstead SB. College student stress: the influence of interpersonal relationships on sense of coherence. Stress Health 2007 Oct;23(4):215-229. [doi: 10.1002/smi.1139]
6. Liu S, Zhu M, Yu DJ, Rasin A, Young SD. Using real-time social media technologies to monitor levels of perceived stress and emotional state in college students: a web-based questionnaire study. JMIR Ment Health 2017 Jan 10;4(1):e2. [doi: 10.2196/mental.5626] [Medline: 28073737]
7. Sowislo JF, Orth U. Does low self-esteem predict depression and anxiety? A meta-analysis of longitudinal studies. Psychol Bull 2013 Jan;139(1):213-240. [doi: 10.1037/a0028931] [Medline: 22730921]
8. Manna G, Falgares G, Ingoglia S, Como M, De SS. The relationship between self-esteem, depression and anxiety: comparing vulnerability and scar model in the Italian context. Mediterr J Clin Psychol 2016;4(3):1619. [doi: 10.6092/2282-1619/2016.4.1328]
9. Orth U, Robins RW, Meier LL. Disentangling the effects of low self-esteem and stressful events on depression: findings from three longitudinal studies. J Pers Soc Psychol 2009 Aug;97(2):307-321. [doi: 10.1037/a0015645] [Medline: 19634977]
10. Liu CH, Stevens C, Wong SH, Yasui M, Chen JA. The prevalence and predictors of mental health diagnoses and suicide among U.S. college students: implications for addressing disparities in service use. Depress Anxiety 2019 Jan;36(1):8-17 [FREE Full text] [doi: 10.1002/da.22830] [Medline: 30188598]
11. Baum A. Stress, intrusive imagery, and chronic distress. Health Psychol 1990;9(6):653-675. [doi: 10.1037/0278-6133.9.6.653]
12. Leary M, Baumeister R. The nature and function of self-esteem: sociometer theory. Adv Exp Soc Psychol 2000;32:1-62. [doi: 10.1016/S0065-2601(00)80003-9]
13. Kroenke K, Spitzer RL, Williams JBW, Löwe B. An ultra-brief screening scale for anxiety and depression: the PHQ-4. Psychosomatics 2009 Dec;50(6):613-621. [doi: 10.1176/appi.psy.50.6.613] [Medline: 19996233]
14. Arroll B, Goodyear-Smith F, Crengle S, Gunn J, Kerse N, Fishman T, et al. Validation of PHQ-2 and PHQ-9 to screen for major depression in the primary care population. Ann Fam Med 2010;8(4):348-353. [doi: 10.1370/afm.1139] [Medline: 20644190]
15. Kuster F, Orth U, Meier LL. Rumination mediates the prospective effect of low self-esteem on depression: a five-wave longitudinal study. Pers Soc Psychol Bull 2012 Jun;38(6):747-759. [doi: 10.1177/0146167212437250] [Medline: 22394574]
16. Long EE, Young JF, Hankin BL. Temporal dynamics and longitudinal co-occurrence of depression and different anxiety syndromes in youth: Evidence for reciprocal patterns in a 3-year prospective study. J Affect Disord 2018 Jul;234:20-27 [FREE Full text] [doi: 10.1016/j.jad.2018.02.074] [Medline: 29522939]
17. Zubin J, Spring B. Vulnerability: a new view of schizophrenia. J Abnorm Psychol 1977;86(2):103-126. [doi: 10.1037/0021-843x.86.2.103]

18. Orth U, Robins RW. Understanding the link between low self-esteem and depression. Curr Dir Psychol Sci 2013 Dec 03;22(6):455-460. [doi: 10.1177/0963721413492763]
19. Clark DM, Wells A. Social Phobia: Diagnosis, Assessment and Treatment. New York: Guilford Press; 1995.
20. Hodson KJ, McManus FV, Clark DM, Doll H. Can Clark and Wells' (1995) cognitive model of social phobia be applied to young people? Behav Cogn Psychother 2008 Jul 01;36(4):449-461. [doi: 10.1017/s1352465808004487]
21. Coyne JC, Gallo SM, Klinkman MS, Calarco MM. Effects of recent and past major depression and distress on self-concept and coping. J Abnorm Psychol 1998;107(1):86-96. [doi: 10.1037/0021-843x.107.1.86]
22. Shahar G, Davidson L. Depressive symptoms erode self-esteem in severe mental illness: a three-wave, cross-lagged study. J Consult Clin Psychol 2003;71(5):890-900. [doi: 10.1037/0022-006x.71.5.890]
23. Dinga R, Schmaal L, Penninx BW, van Tol MJ, Veltman DJ, van Velzen L, et al. Evaluating the evidence for biotypes of depression: methodological replication and extension of Drysdale et al. (2017). Neuroimage Clin 2019;22:101796. [doi: 10.1016/j.nicl.2019.101796] [Medline: 30935858]
24. Camerer CF, Dreber A, Holzmeister F, Ho T, Huber J, Johannesson M, et al. Evaluating the replicability of social science experiments in Nature and Science between 2010 and 2015. Nat Hum Behav 2018 Sep;2(9):637-644. [doi: 10.1038/s41562-018-0399-z] [Medline: 31346273]
25. Shiffman S, Stone AA, Hufford MR. Ecological momentary assessment. Annu Rev Clin Psychol 2008 Apr;4(1):1-32. [doi: 10.1146/annurev.clinpsy.3.022806.091415] [Medline: 18509902]
26. Smyth JM, Smyth JM. Ecological momentary assessment research in behavioral medicine. J Happiness Stud 2003;4(1):35-52. [doi: 10.1023/A:1023657221954]
27. Granger C. Causality, cointegration, and control. J Econ Dyn Control 1988 Jun;12(2-3):551-559. [doi: 10.1016/0165-1889(88)90055-3]
28. Runge J. Causal network reconstruction from time series: from theoretical assumptions to practical estimation. Chaos 2018 Jul;28(7):075310. [doi: 10.1063/1.5025050] [Medline: 30070533]
29. Runge J, Nowack P, Kretschmer M, Flaxman S, Sejdinovic D. Detecting and quantifying causal associations in large nonlinear time series datasets. Sci Adv 2019 Nov;5(11) [FREE Full text] [doi: 10.1126/sciadv.aau4996] [Medline: 31807692]
30. Dartmouth College. Interested in participating in a psychology experiment? URL: https://pbs.dartmouth.edu/research/interested-participating-psychology-experiment [accessed 2019-11-20]
31. Huckins JF, daSilva AW, Wang R, Wang W, Hedlund EL, Murphy EI, et al. Fusing mobile phone sensing and brain imaging to assess depression in college students. Front Neurosci 2019;13:248. [doi: 10.3389/fnins.2019.00248] [Medline: 30949024]
32. Wang R, Chen F, Chen Z, Li T, Harari G, Tignor S. StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '14. New York, New York, USA: ACM Press; 2014 Presented at: UBICOMP '14,; September 13 - 17, 2014; Seattle, WA, USA. [doi: 10.1145/2632048.2632054]
33. Heatherton TF, Polivy J. Development and validation of a scale for measuring state self-esteem. J Pers Soc Psychol 1991;60(6):895-910. [doi: 10.1037/0022-3514.60.6.895]
34. Likert R. A technique for the measurement of attitudes. Arch Psychol 1932;22:55.
35. Runge J. Conditional independence testing based on a nearest-neighbor estimator of conditional mutual information. arXiv 2017 Sep 05;84.
36. TIgramite 4.1 documentation. Tigramite URL: https://jakobrunge.github.io/tigramite/ [accessed 2019-11-20]
37. Runge J. Belmont Forum. 2017. Causal inference and complex network methods for the geosciences URL: https://www.belmontforum.org/wp-content/uploads/2018/04/Causal-Inference-and-Complex-Network-Methods-for-the-Geosciences.pdf [accessed 2019-11-20]
38. Spirtes P, Glymour C. An algorithm for fast recovery of sparse causal graphs. Soc Sci Comput Rev 2016 Aug 18;9(1):62-72. [doi: 10.1177/089443939100900106]
39. Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D. qgraph: network visualizations of relationships in psychometric data. J Stat Soft 2012;48(4). [doi: 10.18637/jss.v048.i04]
40. Nima AA, Rosenberg P, Archer T, Garcia D. Anxiety, affect, self-esteem, and stress: mediation and moderation effects on depression. PLoS One 2013;8(9):e73265. [doi: 10.1371/journal.pone.0073265] [Medline: 24039896]
41. Wang R, Wang W, daSilva A, Huckins JF, Kelley WM, Heatherton TF, et al. Tracking depression dynamics in college students using mobile phone and wearable sensing. Proc ACM Interact Mob Wearable Ubiquitous Technol 2018 Mar 26;2(1):1-26. [doi: 10.1145/3191775]
42. Sabshin M. Depression: clinical, experimental and theoretical aspects. Arch Gen Psychiatry 1968 Dec 01;19(6):766. [doi: 10.1001/archpsyc.1968.01740120126024]
43. Metalsky GI, Joiner TE. Vulnerability to depressive symptomatology: a prospective test of the diathesis-stress and causal mediation components of the hopelessness theory of depression. J Pers Soc Psychol 1992;63(4):667-675. [doi: 10.1037/0022-3514.63.4.667]
44. Mu W, Luo J, Rieger S, Trautwein U, Roberts B. The relationship between self-esteem and depression when controlling for neuroticism. Collabra Psychol 2019;5:11. [doi: 10.1525/collabra.204]

45. Obuchi M, Sasaki W, Okoshi T, Nakazawa J, Tokuda H. Investigating interruptibility at activity breakpoints using smartphone activity recognition API. In: UBICOMP/ISWC '16 ADJUNCT. New York, New York, USA: ACM Press; 2016 Presented at: UBICOMP; September 12-16, 2016; Heidelberg, Germany p. 1602-1607. [doi: 10.1145/2968219.2968556]
46. Pejovic V, Musolesi M. InterruptMe: designing intelligent prompting mechanisms for pervasive applications. In: UBICOMP '14. New York, New York, USA: ACM Press; 2014 Presented at: UBICOMP; September 13-17, 2014; Seattle, WA, USA p. 897-908. [doi: 10.1145/2632048.2632062]

## Abbreviations

**C1:** cohort 1
**C2:** cohort 2
**EMA:** ecological momentary assessment
**GAD-2:** Generalized Anxiety Disorder-2
**MCI:** momentary conditional independence
**PCMCI:** Peter and Clark Momentary Conditional Independence
**PHQ:** Patient Health Questionnaire

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Review

# Peer Support in Mental Health: Literature Review

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## Abstract

**Background:** A growing gap has emerged between people with mental illness and health care professionals, which in recent years has been successfully closed through the adoption of peer support services (PSSs). Peer support in mental health has been variously defined in the literature and is simply known as the help and support that people with lived experience of mental illness or a learning disability can give to one another. Although PSSs date back to several centuries, it is only in the last few decades that these services have formally evolved, grown, and become an integral part of the health care system. Debates around peer support in mental health have been raised frequently in the literature. Although many authors have emphasized the utmost importance of incorporating peer support into the health care system to instill hope; to improve engagement, quality of life, self-confidence, and integrity; and to reduce the burden on the health care system, other studies suggest that there are neutral effects from integrating PSSs into health care systems, with a probable waste of resources.

**Objective:** In this general review, we aimed to examine the literature, exploring the evolution, growth, types, function, generating tools, evaluation, challenges, and the effect of PSSs in the field of mental health and addiction. In addition, we aimed to describe PSSs in different, nonexhaustive contexts, as shown in the literature, that aims to draw attention to the proposed values of PSSs in such fields.

**Methods:** The review was conducted through a general search of the literature on MEDLINE, Google Scholar, EMBASE, Scopus, Chemical Abstracts, and PsycINFO. Search terms included peer support, peer support in mental health, social support, peer, family support, and integrated care.

**Results:** There is abundant literature defining and describing PSSs in different contexts as well as tracking their origins. Two main transformational concepts have been described, namely, intentional peer support and transformation from patients to peer support providers. The effects of PSSs are extensive and integrated into different fields, such as forensic PSSs, addiction, and mental health, and in different age groups and mental health condition severity. Satisfaction of and challenges to PSS integration have been clearly dependent on a number of factors and consequently impact the future prospect of this workforce.

**Conclusions:** There is an internationally growing trend to adopt PSSs within addiction and mental health services, and despite the ongoing challenges, large sections of the current literature support the inclusion of peer support workers in the mental health care workforce. The feasibility and maintenance of a robust PSS in health care would only be possible through collaborative efforts and ongoing support and engagement from all health care practitioners, managers, and other stakeholders.

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**KEYWORDS**

peer support; peer support workers; mental illness and addiction; social support; literature review

## Introduction

Peer support services (PSSs) are novel interventions recently adopted in mental health systems worldwide. It is believed, however, that PSSs date back to more than three centuries to the moral treatment era [1], albeit on an informal basis. Diverse definitions and classifications for PSSs have been provided in the literature [2-4], and numerous reports have praised and supported the service provided by peer support workers (PSWs) [5-8]. However, other literature suggests the neutral effects of PSSs, with weak associated evidence to support such services [9,10]. The potential impact of PSWs on their peers [11-14] has received considerable attention in the literature.

PSSs have been introduced in different contexts, such as family PSWs [15-19], the forensic field [20,21], and online PSSs. A considerable number of strategies were proposed to generate an effective PSS in the mental health field amid a number of associated concerns and challenges [22-25].

## Methods

This general review sheds light on PSWs' experiences, benefits, challenges, opportunities to expand access to quality addiction, and mental health care using PSSs. The review was conducted through a general search of the literature on MEDLINE, Google Scholar, EMBASE, Scopus, Chemical Abstracts, and PsycINFO. Search terms included peer support, peer support in mental health, social support, peer, family support, and integrated care. We began the review with an examination of the definitions, origins, and types of peer support contributions and within different clinical contexts, aiming at deepening the view to the diverse effects of such a workforce. We then continued with examining the transition from a patient role to a PSW role and their incorporation into mental health systems. Thereafter, we provided a conceptual framework for the effects of peer support and stigma in relation to PSWs. We concluded the review by examining the benefits and challenges associated with PSSs and provided a commentary on future directions for PSSs in mental health.

## Results

### Definitions

Peer support has diverse meanings in the literature. For example, it is a *system of giving and receiving help founded on key principles of respect, shared responsibility, and an agreement of what is helpful* [26]. A *peer* is defined as *an equal*, someone with whom one shares demographic or social similarities, whereas *support* refers to "the kind of deeply felt empathy, encouragement, and assistance that people with shared experiences can offer one another within a reciprocal relationship" [3]. The Mental Health Foundation in the United Kingdom defined peer support in mental health as "the help and support that people with lived experience of a mental illness or a learning disability can give to one another" [27]. Peer employees were also defined as "individuals who fill designated unique peer positions as well as peers who are hired into traditional MH positions" [28]. In 1976, authors defined self-help groups as "voluntary small group structures for mutual aid in the accomplishment of a specific purpose...usually formed by peers who have come together for mutual assistance in satisfying a common need, overcoming a common handicap or life-disrupting problem, and bringing about desired social and/or personal change" [28]. Although the mutual relationship was sometimes overlooked and rather described as an asymmetric or nearly one-directional relationship [29], it is emphasized upon as 1 of the 4 main tasks for peer support accomplishments, which are mutuality, connection, worldwide, and moving toward rather than moving away [30].

### Origin and Growth of Peer Support

Davidson et al [11] have expressed the paradigm that calls for new models of community-based practice, which turned away from case management and from conceptualizing old practices under new terms. In the 1990s, peer support was formally introduced as a service in community mental health care. However, there is evidence of its practice throughout history, including during the moral treatment era in France at the end of the 18th century [1]. Recently, peer support has been rapidly growing in many countries and could attract a considerable amount of research [22]. Although Lunatic Friends' Society is known as the earliest peer support group in mental health, which was founded in England in the middle of the 19th century [31], self-help groups were described as the oldest and most pervasive of peer support types [28]. Some peer-run groups also formed in Germany in the late 19th century, which protested on involuntary confinement laws. In addition to this, several individuals in the 18th and 19th centuries publicized their protests about their treatment in autobiographies and petitions [32]. The origin of peer support even reaches further back than the earliest asylums [33]. Some authors suggest that peer support is not based on psychiatric models and diagnostic criteria [3]; however, it is about "understanding another's situation empathically through the shared experience of emotional and psychological pain" [34]. In the United States, the start of legitimacy for peer support was ignited in 2007 by considering the conditions under which PSSs could be reimbursed by Medicaid [35]. Although this reform was entailing a recovery model, which has been adopted by health care providers and stakeholders in many "English-speaking" countries, it was not the case in many other countries, in which this reform was yet to be well formulated [36].

### Transformational Concepts in Peer Support Service

#### *Intentional Peer Support: Informal to Formal Peer Support Evolution*

Intentional peer support (IPS) is described as a philosophical descendant of the informal peer support of the ex-patients' movement in the 1970s [3]. It depends on a way of communication that immerses the provider into the recipient experience by stepping back from one's story and being eagerly open to others' stories [30]. In the field of psychiatry, trauma is blamed for playing a pivotal role in the experience, diagnosis, and treatment, and peer support is described as the logical environment for disseminating trauma-informed care (TIC) or service, which enables building relationships based on mutuality, shared power, and respect [37]. In the same context, trauma-informed peer support usually begins with the main question, “What happened to you?” instead of “What is wrong with you?” [30]. TIC is an explanatory model that identifies PSWs sharing lived experiences, ensuring safety and functioning as an advocate, and a liaison to patient management plans, where empowerment and intervention models are strongly emphasized upon [38,39]. The shift from a traditional biomedical model to recovery-oriented practice is meant to perceive trauma as a coping mechanism rather than a pathology [38,40]. This clearly entails training of all service providers for better acknowledgment and comfort in dealing with *trauma survivors*, with an understanding of trauma as an expectation rather than an exception [41]. Although the TIC concept has evolved over the years, it still lacks guidance, training, staff knowledge, and governmental support, which are necessary to ensure successful policy implementation [40]. The role of PSWs also extended to support those at risk of trauma events because of the nature of their work, including child protection workers, who are at risk of posttraumatic stress disorder or anxiety disorder [42]. Although IPS grew from the informal practices of grassroots-initiated peer support, it differs from earlier approaches because it is a theoretically based, manualized approach with clear goals and a fidelity tool for practitioners [14]. It instead focuses on the nature and purpose of the peer support relationship and its attention to skill building to purposefully engage in peer support relationships that promote mutual healing and growth [3]. Transitioning from informal to formal roles provides not only well-formulated expectations of the role but also a better chance to identify the potential conflict of the PSWs’ mixed identity [43].

Research conducted on PSWs has been conceptualized throughout history [22]. Starting with feasibility studies, at the initial stage, it is followed by studies comparing peer staff with nonpeer staff and, finally, the studies that answer questions such as the following:

- Do interventions provided by peers differ from those provided by nonpeers?
- What makes peer support a unique form of service delivery?

If so, to the previous question, what are the active ingredients of these aspects of peer support, and what outcomes can they produce?

Studies that provide answers to the latter set of questions are expected to provide a deeper understanding of the philosophical underpinnings of the IPS concept for PSSs.

### *The Transformation From Patient to Peer Support Providers*

The shift from being a service recipient to a service provider has been contributing as a driving force to restore fundamental human rights, especially among those with serious mental illnesses (SMIs) [22]. Telling the personal lived experience leads to a profound shift, from telling an “illness story” to a “recovery story” [4]. This involved an identity transformation from being perceived as a victim or a patient to a person fully engaged in life with various opportunities ahead [4]. This transition is seen as a gradual process and one that is supported by several other personal changes with expected challenges [44]. Moving a full circle to include PSWs as the service provider has been undertaken by mental health services to further exceed the transformational role, which was primarily the main aim of providing such a service [45]. A liminal identity was given for PSWs as laying between several roles, being service users, friends, and staff. Thus, the professionalism of the PSW role might not be a successful way to ensure individual well-being or to promote the peer support initiative [46]. Thus, successful transitioning from the patient to PSW role involves fundamental functional shifts achieved through overcoming multiple barriers at the personal, health system, and societal levels.

## Effects of Peer Support Service in Different Contexts

Trained PSWs or mentors can use communication behaviors useful to different client groups. Many studies showed the effectiveness and feasibility of applying for peer support as follows:

### *Severe or Serious Mental Illness*

Generally, the evidence for peer support interventions for people with SMIs has been described as moderate to limited with mixed intervention effects [2,47]. On the one hand, adding PSSs to intensive case management teams proved to improve *activation* in terms of knowledge, skills, confidence, and attitudes for managing health and treatment. Hence, patients become healthier, report better quality of life (QOL), engage in more health care practices, and report more treatment satisfaction [48,49]. On the other hand, a systematic review of randomized controlled trials (RCTs) involving adults with SMIs, while showing some evidence of positive effects on measures of hope, recovery, and empowerment at and beyond the end of the PSS intervention in this review, did not show any positive effects on hospitalization, satisfaction, or overall symptoms [10]. Similarly, a Cochrane systematic review of PSSs for people with schizophrenia found inconclusive results, with a high risk of bias in most of the studies and insufficient data to support or refute the PSS for this group [50].

### *Addiction and Drug Users*

In recent years, peer recovery support services have become an accepted part of the treatment for substance use disorders, providing a more extensive array of services that are typically associated with the mutual supportive intervention [51]. This is in contrast to the use of peer support for SMIs where evidence is still developing. The Substance Abuse and Mental Health Services Administration (SAMHSA) defined peer recovery support for substance use disorders as “a set of nonclinical, peer-based activities that engage, educate, and support individuals so that they can make life changes that are necessary to recover from substance use disorders” [51]. Despite the long-term nature of substance abuse, immersion in peer support groups and activities and active engagement in the community are considered the 2 critical predictors of recovery for more than half the dependent substance users [52].

A number of trials studied the peer support effect on drug users, especially in the emergency department [53,54]. Another randomized trial found that a socially focused treatment can affect change in the patient’s social network and hence increase support for abstinence, for example, an increase of one nondrinking friend in the social network is translated into a 27% increase in the probability of reporting abstinence on 90% of days or more at all follow-up visits, which extended to 15 months [55].

### Forensic Peer Support Service

The forensic peer system refers to the engagement of peer specialists who have histories of mental illness as well as criminal justice involvement and who are trained to help other patients sharing similar accounts [20]. As referred to by Davidson and Rowe [20], "Forensic Peer Specialists embody the potential for recovery for people who confront the dual stigmas associated with SMI and criminal justice system involvement."

They offer day-to-day support for those released early from jail by accompanying them to initial probation meetings or treatment appointments and referring them to potential employers and landlords, helping people to negotiate and minimize continuing criminal sanctions and training professional staff on engaging consumers with criminal justice history [20,21]. PSWs with incarceration histories could successfully identify the liminal space in being supportive rather than providing support for the criminal offense, in contrast with the conventional methods that directly confront criminality [56]. In fact, having criminal history is the "critical component" for achieving recovery [56]. Multiple initiatives have been introduced to facilitate a reentry process for people recently released from incarceration, including Forensic Assertive Community Treatment, Assertive Community Treatment, Critical Time Intervention, and Women's Initiative Supporting Health Transitions Clinic, through diverse community support groups involving PSWs [57,58].

### Old Adults

A peer support program undertaken by older community volunteers was effective in improving general and physical health, social functioning, depression parameters, and social support satisfaction, especially in socially isolated, low-income older adults [59]. The Reclaiming Joy Peer Support intervention (a mental health intervention that pairs an older adult volunteer with a participant) has the potential for decreasing depression symptoms and improving QOL indicators for both anxiety and depression [60]. Engaging the community in health research could be of a high value in acknowledging their own health needs [61].

### Youth and Adolescents

Peer support programs are mostly needed for university students, where challenges with loneliness and isolation are well recognized [62]. Hence, a need emerged for training peers to support their peer adolescents with the prospective challenges at this age [63]. Trained peer support students without necessarily having a lived experience were also examined in England [64]. The study included university students measuring the acceptability and impact of the volunteer peer support program through 6 weekly sessions. Students with lower mental well-being were more likely to complete the course, and an improvement in mental well-being was recorded for those who attended more frequently. Overall, peers remain to be an essential source of support for young people experiencing mental health and substance use problems [65].

### Medically and Socially Disadvantaged Subgroups

A peer-led, medical self-management program intervention has been beneficial for medically and socially disadvantaged subgroups [60]. The Reclaiming Joy Peer Support intervention has the potential for increasing QOL and reducing depression in low-income older adults who have physical health conditions [60]. Similarly, for those who are "hardly reached," it was indicated that the PSS provided is even more effective in these marginalized populations [66]. A Health and Recovery Peer program was delivered by mental health peer leaders for people with SMIs, resulting in an improvement in the physical health–related QOL parameters such as physical activity and medication adherence [49]. Peer-delivered and technology-supported interventions are feasible and acceptable and are associated with improvements in psychiatric, medical self-management skills, QOL, and empowerment of older adults with SMIs and or chronic health conditions [67,68].

### Persons With Disabilities

The United Nations' Convention on the Rights of Persons with Disabilities (CRPD) was adopted in 2007 and stated that "persons with disabilities should have equal recognition before the law and the right to exercise their legal capacity" [69-71]. Therefore, a positive emphasis upon the supported decision making and the fight against discrimination is evident through the convention. Nevertheless, these initiatives have been perceived as incomplete considering many challenges such as the community social status and ongoing perceived stigma of people with disabilities (PWDs) [70,72]. "Circle of support" is an elaborate example of an applicable peer support model for PWDs that has helped in decision making and facilitating communication [70,73,74]. This is clearly aligned with the paradigm shift from the biomedical to the socially supportive model of disability, which was provided by CRPD [70].

### Peer Support for Families

Families may act either as sources of understanding and support or stigmatization through ignorance, prejudice, and discrimination, with subsequent negative impact [19]. In addition, the distress and burden associated with caring for a family member with mental illness are evident, where 29% to 60% endure significant psychological distress [17]. Family support can be financial or emotional; however, moral support was perceived as the substantial motivating factor for relatives who are ill [19]. In the last few decades, consistent and growing evidence that supports the inclusion of family members in the treatment and care of their misfortunate relatives has been developed. This has been mainly evident in the youth mental health system that urged the transformation change, which incorporates family members in the health care service provided to their youth [18,75]. Many PSWs have been engaged in family psychoeducation as family peers or parent partners, especially for those with the first episode of psychosis [76]. Although familial education is crucial and needs to be provided through different scales [19], an extensive matching of PSWs and the caregivers has not been perceived as a necessity to create a successful volunteer mentoring relationship [77]. Multiple initiatives have taken place all over the world. In India, a program titled “Saathi” was established for family members of residential and outpatient mental health service users that had dual goals of offering information and developing a peer support mechanism for family members of people with different mental health conditions [19]. In Melbourne, Australia, “Families Helping Families” was developed, where family PSWs are positioned in the service assessment area and in the *inpatient unit* to ensure early involvement [18]. An impressive peer support guide for parents of children or youth with mental health problems is provided by the Canadian Mental Health Association, British Colombia Division [15]. In Ontario, family matters programs are provided through provincial peer support programs [16].

The term “transforming mental health care” entails active involvement of families in orienting the mental health system toward recovery [78]. Family members are to have access to timely and accurate information that promotes learning, self-monitoring, and accountability [79]. The inclusion of family members as partners of the medical service is the new philosophy, with a subsequent shift from the concept of clinic-based practice to a community-based service approach [78].

### *Peer Support Service in Low- and Middle-Income Countries*

Several initiatives took place in low- and middle-income countries, such as in rural Uganda, where a trained peer-led team provided 12 successful training sessions of perinatal service for a group of parents over a 6-month period, which resulted in better maternal well-being and child development, compared with another control group [80]. Similarly, successful community peer groups were conducted in rural India and Nepal, with high feasibility and effectiveness rates, and perceived as “potential alternative to health-worker-led interventions” [81-83]. In addition, adding counseling and social support groups entailing PSWs to the conventional medication treatment for patients with psychotic disorders was tried in a cohort study in Uganda; however, the results were not significantly different from those who received only medications [84]. This might be because of the underpowering of community services offered, compared with the robust medication regimens [85].

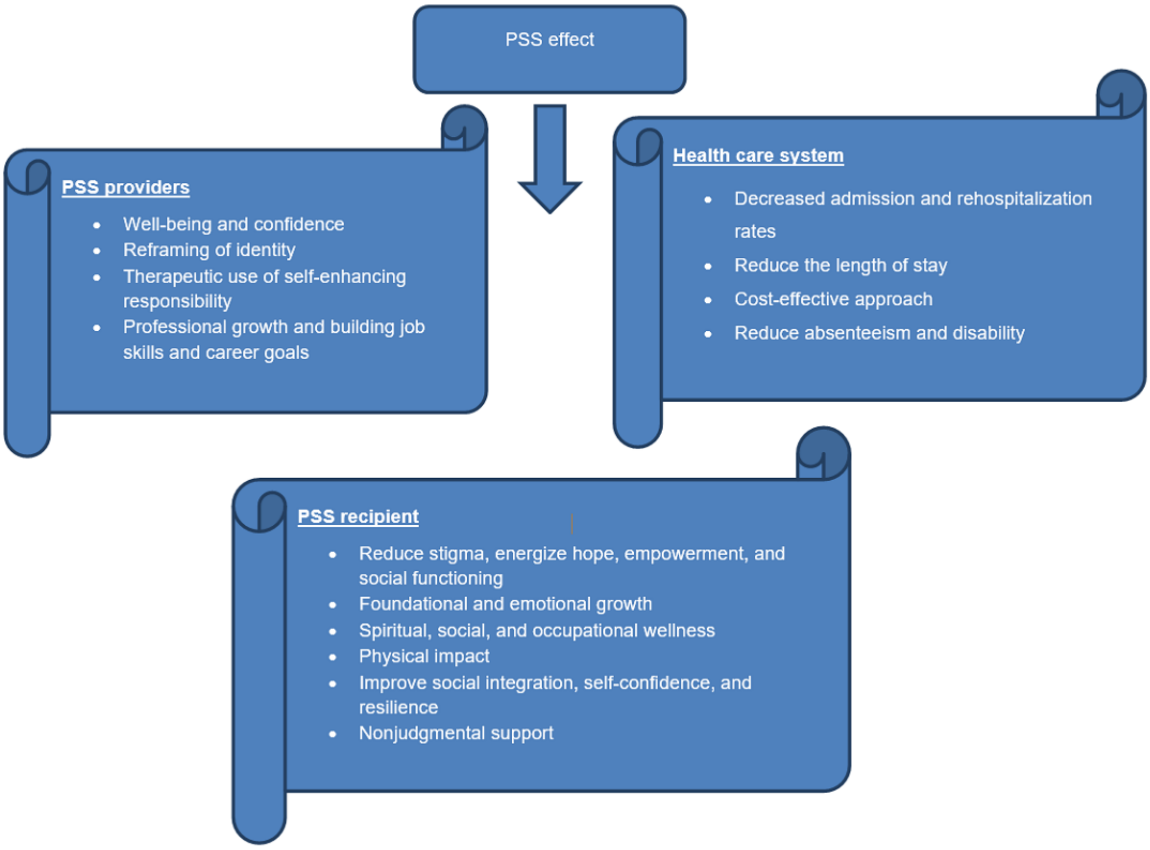
It is evident from the aforementioned information that there is mixed evidence on the effectiveness of PSW interventions in different contexts. For example, for patients with SMIs, systematic reviews suggest that there is some evidence of positive effects on measures of hope, recovery, and empowerment but no positive effects on hospitalization, satisfaction, or overall symptoms [10]. Similarly, for patients with addiction issues, although being involved in a peer network did not reduce social assistance for alcohol, they somewhat increased behavioral and attitudinal support for abstinence as well as involvement with Alcoholics Anonymous [55]. Furthermore, although many observational studies support the PSW role in the other contexts described above, there is a current dearth of literature involving RCTs and systematic reviews reporting on the effectiveness of PSWs in these specific contexts. Thus, there exist opportunities for conducting RCTs in the described contexts.

## The Conceptual Framework for the Effects of Peer Support Service

The conceptual framework is based on empirical evidence, suggesting that the impact of PSWs reflects upon the recipients of such a service [4,76,86-90], the global health system [22,47,76,86,91,92], and the PSWs themselves [13,28,76,93], as shown in Figure 1. The framework has, therefore, been developed by authors through a general review of the literature that examines the effects of PSSs on patients, health care systems, and also PSWs themselves so as to provide evidence-based material supporting all possible effects of PSW roles.

Supportive social relationships can have a dual opposing effect on individuals’ lives, either as a family member or as social and professional networks through sharing their disappointments and pains or their joy and successes [11]. Useful roles for PSSs are identified in many studies. For example, adding 3 peer specialists to a team of 10 intensive case managers provided better QOL with greater satisfaction [12], stigma reduction, and less health service utilization [89,91]. The economic impact of PSSs has been extensively studied in the literature, concluding cost containment for the health care system in terms of reduction of readmission rates, emergency visits, and fewer hospital stays, which altogether substantially exceed the cost of running a peer support program [92]. Moreover, PSWs are looked at as providers of a service at a cheaper cost compared with other health care providers [94,95]. For example, about US $23,000 is paid to PSWs in the United States compared with around US $100,000 for a nurse practitioner [96]. However, a PSS is not posited as a substitute for clinical services, rather it is perceived as an intrapersonal and social service that provides a dual role of effective service and with humanizing care and support [14,26,97]. This role extends to cover PSWs themselves, in terms of improved overall well-being and self-confidence, reframing identity, and enhancing responsibility either toward themselves or their peers [13,93].

**Figure 1.** The conceptual framework for the impact of peer support workers in mental health. MH: mental health; PSS: peer support service; PSW: peer support worker.



Although PSWs can play a variety of tasks, managers who hire them may want to ensure that improving patient activation is included in their range of duties [48]. In 2 concurrent studies, a significant increase in QOL satisfaction, reduction of rehospitalization rates, and reduction in the number of hospital days were recorded when adding PSSs to usual care [22,98]. In another study engaging 31 peer providers in diverse mental health, agencies identified 5 broad domains of wellness, including foundational, emotional, growth and spiritual, social, and occupational wellness [4]. In a systematic literature review for people with SMIs, peer-navigator interventions and self-management were the most promising interventions [47]. PSWs' effects are diversified through sharing in different contexts. For example, positive impacts on the physical health of their peers have been recorded [49]. Peer-based approaches have been used to deliver behavioral weight loss interventions [90]. For young students, structured peer support for depression may have benefits in improving students' mental well-being [64]. In the case of crisis houses, greater satisfaction was achieved through a provided informal PSS [99]. Robust studies, therefore, recommend implementing peer support programs [10,18].

On the other hand, authors found that PSSs met moderate levels of evidence and that effectiveness varied across service types, for example, with "peers in existing clinical roles" was described as being less effective than the "peer staff added to traditional services" and "peer staff delivering structured curricula" [3]. Other reviews suggested that current evidence does not support recommendations or mandatory requirements from policy makers to offer programs for peer support [9,10].

## Peer Support Workers' Satisfaction and Challenges

PSWs experience different problems alongside their diverse job roles, including low pay, stigma, unclear work roles, alienation, struggling with skill deficits, lack of training opportunities, emotional stress in helping others, and, on top of that, maintaining their personal physical and mental health wellness [100,101]. Researchers found that PSWs experience discrimination and prejudice from nonpeer workers, in addition to the encountered difficulties of how to manage the transition from being a patient to a PSW. As a result, high attrition rates were noted among PSWs in mental health settings [102,103]. Peer job satisfaction is strongly dependent on several factors [100,104,105]. Role clarity and psychological empowerment, organizational culture, and working partnership with peers were the most significant predictors of PSW job satisfaction, while professional prejudice was not perceived as a significant predictor [106,107]. Other studies noted that the main problems were experiencing marginalization, lack of understanding, and a sense of exclusion [108-110]. Payment could also contribute to the amount of satisfaction of PSWs [76], as compensation helps through facilitation and engagement motivation [109]. Nevertheless, it seems that not the payment, which ranged from US $10 to US $20 per hour, but the lack of recognition and acknowledgment are the causes for job nonsatisfaction [104].

An interesting literature review grouped these challenges and barriers facing PSWs during fulfilling their assigned roles into

6 main categories: nature of the innovation, individual professional, service user, social context, organizational context, and economic and political contexts [111].

It is evident from the abovementioned information that the PSW role is challenged at multiple levels, including at the personal, societal, and organizational levels. These challenges have a direct bearing on PSW satisfaction, and the successful integration of the PSW role into the health care system depends to a great extent on how these challenges are overcome.

### Novel Technology in Peer Support Service (Online and Telephone)

Online support groups are usually conducted through bulletin boards, emails, or live chatting software [28]. Online groups are familiar with people whose illnesses are similar to SMIs or affecting the body shape that have forced them to experience embarrassment and social stigmatization [23,24]. Therefore, they split from the social contexts and redirect toward novel ways of help, such as PSWs and online support groups, and web-based communities provided a suitable medium for people with SMIs by following and learning from their peers on the web, which positively helped them to fight against stigma, instilling hope and gaining insight and empowerment for better health control [25]. Increasingly, social media grew as a target for individuals with SMIs, such as schizophrenia, schizoaffective disorder, or bipolar disorder, seeking advice and supporting each other [112-114]. For someone with SMIs, the decision to reach out and connect with others typically occurs at a time of increased instability or when facing significant life challenges [115]. In a qualitative study, popular social media, such as YouTube, appeared useful for allowing people with SMIs to feel less alone, find hope, support each other, and share personal experiences and coping strategies with day-to-day challenges of living with mental illness through listening and posting comments [114]. Mobile phone–based peer support was found to be a feasible and acceptable way to the youngsters during their pregnancy as well as in the postpartum period [116]. In addition, when coupled with frequent face-to-face meetings with PSWs and with "text for support," it could be of high value for patients with different mental illnesses [117]. Although online peer networks actively fight against discrimination and stigma, their accessibility to diverse patients' sectors regarding their income and ethnicity is still questionable [25].

### Future of Peer Support Services

Potential new roles, such as community health workers, peer whole health coaches, peer wellness coaches, and peer navigators, have been suggested for such a workforce [76]. They are described as an "ill-defined potential new layer of professionals" [118]. Through an initiative undertaken by SAMHSA via its "Bringing Recovery Supports to Scale Technical Assistance Center Strategy," a successful identification of abilities and critical knowledge necessarily required for PSWs who provide help and support for those recovering from mental health and substance abuse was noted [76]. At present, peer support is seen as a growing paradigm in many countries, including the United Kingdom, Canada, New Zealand, France, and the Netherlands [103,119]. As an evolving culture, peer support has the opportunity to forge not just mental health system change but social change as well [37]. A novel peer support system termed "Edmonton peer support system" (EPSS) is currently being tested in a randomized controlled pilot trial [117]. In this study, investigators are evaluating the effectiveness of an innovative peer support program that incorporates leadership training, mentorship, recognition, and reward systems for PSWs, coupled with automated daily supportive text messaging, which has proven effectiveness in feasibility trials involving patients with depression and alcohol use disorders [120,121]. Previous studies have examined the effect of PSSs in different contexts, including outpatient departments [122], emergency departments [53,54], community mental health clinics [123,124], and inpatient sites [125]. On the contrary, the EPSS study focuses on patients who have been discharged from acute care hospitals. These patients are being randomized into 1 of the 4 main groups: enrollment in a peer support system, enrollment in a peer support system plus automated daily supportive and reminder text messages, enrollment in automated daily supportive and reminder text messages alone, or treatment as usual follow-up care. The research team hypothesizes that patients who are assigned to a peer support system plus automated daily supportive and reminder text messages will show the best outcome.

Organizations may facilitate peer support through their values, actions, and oversight [119] and through a robust supervision system with available educational access, which could be the adequate path for creating a positive and risk-free environment for PSWs throughout their complex workloads [126]. On the other hand, ethics committees play essential roles in the inclusion of PSWs in applied research studies by avoiding repetition of the work of other trusted agencies and considering the ethical validity of consent procedures for peer support interventions [127].

## Discussion

There is an internationally growing trend to adopt PSSs within addiction and mental health services, and despite the ongoing challenges, large sections of the current literature support the inclusion of the PSWs into the mental health care workforce. The literature suggests that the benefits of PSSs impact not only the recipients of mental health services but also extend to the PSWs and the whole health care system. Although the expected benefits of PSSs might be directly measured in terms of service utilization or patient improvement indicators, this could also extend to include wellness and empowerment for PSWs, who may still be fragile, vulnerable, and in need of ongoing acknowledgment and recognition. Thus, the potential for PSSs to be embedded into routine care and the opportunities for the development of innovative models of care for addiction and mental health patients such as the EPSS, which incorporates PSSs and supportive text messaging [117], are evidently a high valued priority. However, the feasibility and maintenance of a robust PSS in health care would only be possible through collaborative efforts and ongoing support and engagement from all health care practitioners, managers, and other stakeholders.

This literature review has several limitations. First, the review is not a systematic review or meta-analysis, and as such, there were no well-defined inclusion or exclusion criteria of studies, which potentially could lead to the exclusion of some essential related studies. Second, the search was conducted in English publications only. Consequently, there is a high probability of missing critical related publications published in non-English languages. Finally, as the review depended mainly on the available literature from the aforementioned sources, which showed marked variability in their design and covered diverse ideas under the central theme, the different weights for each idea throughout the review could be noted.

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## Conflicts of Interest

None declared.

## References

1. Weiner DB. The apprenticeship of Philippe Pinel: a new document, 'observations of Citizen Pussin on the insane'. Am J Psychiatry 1979 Sep;136(9):1128-1134. [doi: 10.1176/ajp.136.9.1128] [Medline: 382874]
2. Chinman M, George P, Dougherty RH, Daniels AS, Ghose SS, Swift A, et al. Peer support services for individuals with serious mental illnesses: assessing the evidence. Psychiatr Serv 2014 Apr 1;65(4):429-441. [doi: 10.1176/appi.ps.201300244] [Medline: 24549400]
3. Penney D. Advocates for Human Potential. 2018. Defining 'Peer Support': Implications for Policy, Practice, and Research URL: https://www.ahpnet.com/AHPNet/media/AHPNetMediaLibrary/White%20Papers/DPenney_Defining_peer_support_2018_Final.pdf [accessed 2019-03-30]
4. Moran GS, Russinova Z, Gidugu V, Yim JY, Sprague C. Benefits and mechanisms of recovery among peer providers with psychiatric illnesses. Qual Health Res 2012 Mar;22(3):304-319. [doi: 10.1177/1049732311420578] [Medline: 21900694]
5. Clarke GN, Herinckx HA, Kinney RF, Paulson RI, Cutler DL, Lewis K, et al. Psychiatric hospitalizations, arrests, emergency room visits, and homelessness of clients with serious and persistent mental illness: findings from a randomized trial of two ACT programs vs. usual care. Ment Health Serv Res 2000 Sep;2(3):155-164. [doi: 10.1023/a:1010141826867] [Medline: 11256724]
6. Davidson L, Shahar G, Stayner DA, Chinman MJ, Rakfeldt J, Tebes JK. Supported socialization for people with psychiatric disabilities: lessons from a randomized controlled trial. J Commun Psychol 2004;32(4):453-477. [doi: 10.1002/jcop.20013]
7. O'Donnell M, Parker G, Proberts M, Matthews R, Fisher D, Johnson B, et al. A study of client-focused case management and consumer advocacy: the Community and Consumer Service Project. Aust N Z J Psychiatry 1999 Oct;33(5):684-693. [doi: 10.1080/j.1440-1614.1999.00629.x] [Medline: 10544992]
8. Solomon P, Draine J. The efficacy of a consumer case management team: 2-year outcomes of a randomized trial. J Ment Health Adm 1995;22(2):135-146. [doi: 10.1007/bf02518754] [Medline: 10142127]
9. Pitt V, Lowe D, Hill S, Prictor M, Hetrick SE, Ryan R, et al. Consumer-providers of care for adult clients of statutory mental health services. Cochrane Database Syst Rev 2013 Mar 28(3):CD004807. [doi: 10.1002/14651858.CD004807.pub2] [Medline: 23543537]
10. Lloyd-Evans B, Mayo-Wilson E, Harrison B, Istead H, Brown E, Pilling S, et al. A systematic review and meta-analysis of randomised controlled trials of peer support for people with severe mental illness. BMC Psychiatry 2014 Feb 14;14:39 [FREE Full text] [doi: 10.1186/1471-244X-14-39] [Medline: 24528545]
11. Davidson L, Tondora J, Staeheli M, Martha C, Maria F, Jennifer M, et al. Recovery guides: an emerging model of community-based care for adults with psychiatric disabilities. In: Lightburn A, Sessions P, editors. Handbook Of Community-based Clinical Practice. London: Oxford University Press; 2005:476-501.
12. Felton CJ, Stastny P, Shern DL, Blanch A, Donahue SA, Knight E, et al. Consumers as peer specialists on intensive case management teams: impact on client outcomes. Psychiatr Serv 1995 Oct;46(10):1037-1044. [doi: 10.1176/ps.46.10.1037] [Medline: 8829785]
13. Beales A, Wilson J. Peer support – the what, why, who, how and now. J Ment Health Train Educ Prac 2015;10(5):314-324. [doi: 10.1108/JMHTEP-03-2015-0013]
14. MacNeil C, Mead S. A narrative approach to developing standards for trauma-informed peer support. Am J Eval 2016;26(2):231-244. [doi: 10.1177/1098214005275633]
15. Canadian Mental Health Association.: Canadian Mental Health Association, BC Division; 2007. Peer Support Guide: For Parents of Children or Youth with Mental Health Problems URL: https://cmha.bc.ca/wp-content/uploads/2016/07/ParentPeerSupportGuide.pdf [accessed 2020-02-29]
16. Mood Disorders Association of Ontario. Family Matters Peer Support and Recovery Program URL: https://www.mooddisorders.ca/family-matters-programs [accessed 2020-02-29]

17. Quinn J, Barrowclough C, Tarrier N. The Family Questionnaire (FQ): a scale for measuring symptom appraisal in relatives of schizophrenic patients. Acta Psychiatr Scand 2003 Oct;108(4):290-296. [doi: 10.1034/j.1600-0447.2003.00156.x] [Medline: 12956830]
18. Leggatt M, Woodhead G. Family peer support work in an early intervention youth mental health service. Early Interv Psychiatry 2016 Oct;10(5):446-451. [doi: 10.1111/eip.12257] [Medline: 26213221]
19. Mahomed F, Stein MA, Chauhan A, Pathare S. 'They love me, but they don't understand me': Family support and stigmatisation of mental health service users in Gujarat, India. Int J Soc Psychiatry 2019 Feb;65(1):73-79. [doi: 10.1177/0020764018816344] [Medline: 30518280]
20. Davidson L, Rowe M. The Family-Run Executive Director Leadership Association (FREDLA). 5600 Fishers Ln, Rockville, MD 20857: The CMHS National GAINS Center; 2008 May. Peer Support within Criminal Justice Settings: The Role of Forensic Peer Specialists URL: https://fredla.org/wp-content/uploads/2016/01/davidsonrowe_peersupport1.pdf [accessed 2020-03-01]
21. Short R, Woods-Nyce K, Cross SL, Hurst MA, Gordish L, Raia J. The impact of forensic peer support specialists on risk reduction and discharge readiness in a psychiatric facility: A five-year perspective. Int J Psychosoc Rehabil 2012;16(2):3-10 [FREE Full text]
22. Davidson L, Bellamy C, Guy K, Miller R. Peer support among persons with severe mental illnesses: a review of evidence and experience. World Psychiatry 2012 Jun;11(2):123-128 [FREE Full text] [doi: 10.1016/j.wpsyc.2012.05.009] [Medline: 22654945]
23. Berger M, Wagner TH, Baker LC. Internet use and stigmatized illness. Soc Sci Med 2005 Oct;61(8):1821-1827. [doi: 10.1016/j.socscimed.2005.03.025] [Medline: 16029778]
24. Highton-Williamson E, Priebe S, Giacco D. Online social networking in people with psychosis: a systematic review. Int J Soc Psychiatry 2015 Feb;61(1):92-101. [doi: 10.1177/0020764014556392] [Medline: 25381145]
25. Naslund JA, Aschbrenner KA, Marsch LA, Bartels SJ. The future of mental health care: peer-to-peer support and social media. Epidemiol Psychiatr Sci 2016 Apr;25(2):113-122 [FREE Full text] [doi: 10.1017/S2045796015001067] [Medline: 26744309]
26. Mead S, Hilton D, Curtis L. Peer support: a theoretical perspective. Psychiatr Rehabil J 2001;25(2):134-141. [doi: 10.1037/h0095032] [Medline: 11769979]
27. Mental Health Foundation. Peer Support URL: https://www.mentalhealth.org.uk/a-to-z/p/peer-support [accessed 2020-02-29]
28. Solomon P. Peer support/peer provided services underlying processes, benefits, and critical ingredients. Psychiatr Rehabil J 2004;27(4):392-401. [doi: 10.2975/27.2004.392.401] [Medline: 15222150]
29. Davidson L, Chinman M, Sells D, Rowe M. Peer support among adults with serious mental illness: a report from the field. Schizophr Bull 2006 Jul;32(3):443-450 [FREE Full text] [doi: 10.1093/schbul/sbj043] [Medline: 16461576]
30. Mead S. Intentional Peer Support: An Alternative Approach. West Chesterfield, NH: Intentional Peer Support; 2014.
31. Sunderland K, Mishkin W, Peer Leadership Group, Mental Health Commission of Canada. Mental Health Commission of Canada. 2013. Guidelines for the Practice and Training of Peer Support URL: https://www.mentalhealthcommission.ca/sites/default/files/peer_support_guidelines.pdf.pdf [accessed 2020-02-29]
32. Peterson D. A Mad People's History of Madness. Pittsburgh, PA: University Of Pittsburgh Press; 1981.
33. Shaw C. Together: A leading UK mental health charity. 2014. Peer Support in Secure Services: Final Report URL: https://www.together-uk.org/wp-content/uploads/downloads/2014/11/Peer-Support-in-Secure-Settings-Final-Report-4-Nov-14.pdf [accessed 2020-02-28]
34. Mead S. Defining Peer Support. 2003 Mar. URL: http://164.156.7.185/parecovery/documents/DefiningPeerSupport_Mead.pdf [accessed 2020-02-29]
35. Ostrow L, Steinwachs D, Leaf PJ, Naeger S. Medicaid reimbursement of mental health peer-run organizations: results of a national survey. Adm Policy Ment Health 2017 Jul;44(4):501-511. [doi: 10.1007/s10488-015-0675-4] [Medline: 26219825]
36. Stratford AC, Halpin M, Phillips K, Skerritt F, Beales A, Cheng V, et al. The growth of peer support: an international charter. J Ment Health 2019 Dec;28(6):627-632. [doi: 10.1080/09638237.2017.1340593] [Medline: 28682640]
37. Mead S. Google Docs. PO Box 259, West Chesterfield, NH 03466: Intentional Peer Support; 2001. Peer Support as a Socio-Political Response to Trauma and Abuse URL: https://docs.google.com/document/d/1trJ35i4dXX5AIWRnbg78OaT7-RfPE9_DbPm5kSST9_Q/edit [accessed 2020-02-28]
38. Wilson AM, Hutchinson M, Hurley J. Literature review of trauma-informed care: implications for mental health nurses working in acute inpatient settings in Australia. Int J Ment Health Nurs 2017 Aug;26(4):326-343. [doi: 10.1111/inm.12344] [Medline: 28480568]
39. Goetz SB, Taylor-Trujillo A. A change in culture: violence prevention in an acute behavioral health setting. J Am Psychiatr Nurses Assoc 2012;18(2):96-103. [doi: 10.1177/1078390312439469] [Medline: 22442017]
40. Ashmore TR. Massey University. 2013. The Implementation of Trauma Informed Care in Acute Mental Health Inpatient Units: A Comparative Study URL: https://mro.massey.ac.nz/bitstream/handle/10179/5855/02_whole.pdf [accessed 2020-02-29]
41. Brown VB, Harris M, Fallot R. Moving toward trauma-informed practice in addiction treatment: a collaborative model of agency assessment. J Psychoactive Drugs 2013;45(5):386-393. [doi: 10.1080/02791072.2013.844381] [Medline: 24592664]

42. Guay S, Tremblay N, Goncalves J, Bilodeau H, Geoffrion S. Effects of a peer support programme for youth social services employees experiencing potentially traumatic events: a protocol for a prospective cohort study. BMJ Open 2017 Jun 24;7(6):e014405 [FREE Full text] [doi: 10.1136/bmjopen-2016-014405] [Medline: 28647721]
43. Gillard SG, Edwards C, Gibson SL, Owen K, Wright C. Introducing peer worker roles into UK mental health service teams: a qualitative analysis of the organisational benefits and challenges. BMC Health Serv Res 2013 May 24;13:188 [FREE Full text] [doi: 10.1186/1472-6963-13-188] [Medline: 23705767]
44. Tookey P, Mason K, Broad J, Behm M, Bondy L, Powis J. From client to co-worker: a case study of the transition to peer work within a multi-disciplinary hepatitis c treatment team in Toronto, Canada. Harm Reduct J 2018 Aug 14;15(1):41 [FREE Full text] [doi: 10.1186/s12954-018-0245-7] [Medline: 30107808]
45. Stastny P, Brown C. [Peer specialist: origins, pitfalls and worldwide dissemination]. Vertex 2013;24(112):455-459. [Medline: 24511563]
46. Simpson A, Oster C, Muir-Cochrane E. Liminality in the occupational identity of mental health peer support workers: a qualitative study. Int J Ment Health Nurs 2018 Apr;27(2):662-671 [FREE Full text] [doi: 10.1111/inm.12351] [Medline: 28548455]
47. Cabassa LJ, Camacho D, Vélez-Grau CM, Stefancic A. Peer-based health interventions for people with serious mental illness: a systematic literature review. J Psychiatr Res 2017 Jan;84:80-89. [doi: 10.1016/j.jpsychires.2016.09.021] [Medline: 27701013]
48. Chinman M, Oberman RS, Hanusa BH, Cohen AN, Salyers MP, Twamley EW, et al. A cluster randomized trial of adding peer specialists to intensive case management teams in the Veterans Health Administration. J Behav Health Serv Res 2015 Jan;42(1):109-121 [FREE Full text] [doi: 10.1007/s11414-013-9343-1] [Medline: 23657754]
49. Druss BG, Zhao L, von Esenwein SA, Bona JR, Fricks L, Jenkins-Tucker S, et al. The Health and Recovery Peer (HARP) Program: a peer-led intervention to improve medical self-management for persons with serious mental illness. Schizophr Res 2010 May;118(1-3):264-270 [FREE Full text] [doi: 10.1016/j.schres.2010.01.026] [Medline: 20185272]
50. Chien W, Clifton AV, Zhao S, Lui S. Peer support for people with schizophrenia or other serious mental illness. Cochrane Database Syst Rev 2019 Apr 4;4:CD010880. [doi: 10.1002/14651858.CD010880.pub2] [Medline: 30946482]
51. Reif S, Braude L, Lyman DR, Dougherty RH, Daniels AS, Ghose SS, et al. Peer recovery support for individuals with substance use disorders: assessing the evidence. Psychiatr Serv 2014 Jul;65(7):853-861. [doi: 10.1176/appi.ps.201400047] [Medline: 24838535]
52. Best DW, Lubman DI. The recovery paradigm - a model of hope and change for alcohol and drug addiction. Aust Fam Physician 2012 Aug;41(8):593-597. [Medline: 23145400]
53. Watson DP, Brucker K, McGuire A, Snow-Hill NL, Xu H, Cohen A, et al. Replication of an emergency department-based recovery coaching intervention and pilot testing of pragmatic trial protocols within the context of Indiana's Opioid State Targeted Response plan. J Subst Abuse Treat 2020 Jan;108:88-94. [doi: 10.1016/j.jsat.2019.06.002] [Medline: 31200985]
54. McGuire AB, Powell KG, Treitler PC, Wagner KD, Smith KP, Cooperman N, et al. Emergency department-based peer support for opioid use disorder: emergent functions and forms. J Subst Abuse Treat 2020 Jan;108:82-87. [doi: 10.1016/j.jsat.2019.06.013] [Medline: 31280928]
55. Litt MD, Kadden RM, Kabela-Cormier E, Petry N. Changing network support for drinking: initial findings from the network support project. J Consult Clin Psychol 2007 Aug;75(4):542-555. [doi: 10.1037/0022-006X.75.4.542] [Medline: 17663609]
56. Barrenger SL, Hamovitch EK, Rothman MR. Enacting lived experiences: peer specialists with criminal justice histories. Psychiatr Rehabil J 2019 Mar;42(1):9-16. [doi: 10.1037/prj0000327] [Medline: 30265065]
57. Angell B, Matthews E, Barrenger S, Watson AC, Draine J. Engagement processes in model programs for community reentry from prison for people with serious mental illness. Int J Law Psychiatry 2014;37(5):490-500 [FREE Full text] [doi: 10.1016/j.ijlp.2014.02.022] [Medline: 24650496]
58. Thomas K, Wilson JL, Bedell P, Morse DS. 'They didn't give up on me': a women's transitions clinic from the perspective of re-entering women. Addict Sci Clin Pract 2019 Apr 2;14(1):12 [FREE Full text] [doi: 10.1186/s13722-019-0142-8] [Medline: 30935408]
59. Kim SH. [Effects of a volunteer-run peer support program on health and satisfaction with social support of older adults living alone]. J Korean Acad Nurs 2012 Aug;42(4):525-536. [doi: 10.4040/jkan.2012.42.4.525] [Medline: 22972213]
60. Chapin RK, Sergeant JF, Landry S, Leedahl SN, Rachlin R, Koenig T, et al. Reclaiming joy: pilot evaluation of a mental health peer support program for older adults who receive Medicaid. Gerontologist 2013 Apr;53(2):345-352. [doi: 10.1093/geront/gns120] [Medline: 22936540]
61. Ahmed SM, Palermo AS. Community engagement in research: frameworks for education and peer review. Am J Public Health 2010 Aug;100(8):1380-1387. [doi: 10.2105/AJPH.2009.178137] [Medline: 20558798]
62. Student Minds. 2014. Grand Challenges in Student Mental Health URL: https://www.studentminds.org.uk/uploads/3/7/8/4/3784584/grand_challenges_report_for_public.pdf [accessed 2020-02-29]
63. Davies EB, Wardlaw J, Morriss R, Glazebrook C. An experimental study exploring the impact of vignette gender on the quality of university students' mental health first aid for peers with symptoms of depression. BMC Public Health 2016 Feb 25;16:187 [FREE Full text] [doi: 10.1186/s12889-016-2887-2] [Medline: 26911725]

64. Byrom N. An evaluation of a peer support intervention for student mental health. J Ment Health 2018 Jun;27(3):240-246. [doi: 10.1080/09638237.2018.1437605] [Medline: 29451411]
65. Lubman DI, Cheetham A, Jorm AF, Berridge BJ, Wilson C, Blee F, et al. Australian adolescents' beliefs and help-seeking intentions towards peers experiencing symptoms of depression and alcohol misuse. BMC Public Health 2017 Aug 16;17(1):658 [FREE Full text] [doi: 10.1186/s12889-017-4655-3] [Medline: 28814325]
66. Sokol R, Fisher E. Peer support for the hardly reached: a systematic review. Am J Public Health 2016 Jul;106(7):e1-e8. [doi: 10.2105/AJPH.2016.303180] [Medline: 27196645]
67. Fortuna KL, DiMilia PR, Lohman MC, Bruce ML, Zubritsky CD, Halaby MR, et al. Feasibility, acceptability, and preliminary effectiveness of a peer-delivered and technology supported self-management intervention for older adults with serious mental illness. Psychiatr Q 2018 Jun;89(2):293-305 [FREE Full text] [doi: 10.1007/s11126-017-9534-7] [Medline: 28948424]
68. Whiteman KL, Naslund JA, DiNapoli EA, Bruce ML, Bartels SJ. Systematic review of integrated general medical and psychiatric self-management interventions for adults with serious mental illness. Psychiatr Serv 2016 Nov 1;67(11):1213-1225 [FREE Full text] [doi: 10.1176/appi.ps.201500521] [Medline: 27301767]
69. Pathare S, Shields LS. Supported decision-making for persons with mental illness: a review. Pub Health Rev 2012;34(15). [doi: 10.1007/bf03391683]
70. Mahomed F, Stein MA, Patel V. Involuntary mental health treatment in the era of the United Nations Convention on the Rights of Persons with Disabilities. PLoS Med 2018 Oct;15(10):e1002679 [FREE Full text] [doi: 10.1371/journal.pmed.1002679] [Medline: 30335757]
71. Morrissey F. The United Nations Convention on the Rights of Persons with Disabilities: a new approach to decision-making in mental health law. Eur J Health Law 2012 Dec;19(5):423-440. [doi: 10.1163/15718093-12341237] [Medline: 23198484]
72. Szmukler G. 'Capacity', 'best interests', 'will and preferences' and the UN Convention on the Rights of Persons with Disabilities. World Psychiatry 2019 Feb;18(1):34-41 [FREE Full text] [doi: 10.1002/wps.20584] [Medline: 30600630]
73. Jeste DV, Eglit GM, Palmer BW, Martinis JG, Blanck P, Saks ER. Supported decision making in serious mental illness. Psychiatry 2018;81(1):28-40 [FREE Full text] [doi: 10.1080/00332747.2017.1324697] [Medline: 29494793]
74. Craigie J. A fine balance: reconsidering patient autonomy in light of the UN convention on the rights of persons with disabilities. Bioethics 2015 Jul;29(6):398-405. [doi: 10.1111/bioe.12133] [Medline: 25492591]
75. Henderson JL, Cheung A, Cleverley K, Chaim G, Moretti ME, de Oliveira C, et al. Integrated collaborative care teams to enhance service delivery to youth with mental health and substance use challenges: protocol for a pragmatic randomised controlled trial. BMJ Open 2017 Feb 6;7(2):e014080 [FREE Full text] [doi: 10.1136/bmjopen-2016-014080] [Medline: 28167747]
76. Gagne CA, Finch WL, Myrick KJ, Davis LM. Peer workers in the behavioral and integrated health workforce: opportunities and future directions. Am J Prev Med 2018 Jun;54(6 Suppl 3):S258-S266 [FREE Full text] [doi: 10.1016/j.amepre.2018.03.010] [Medline: 29779550]
77. Smith R, Greenwood N. The impact of volunteer mentoring schemes on carers of people with dementia and volunteer mentors: a systematic review. Am J Alzheimers Dis Other Demen 2014 Feb;29(1):8-17. [doi: 10.1177/1533317513505135] [Medline: 24085253]
78. Huang L, Stroul B, Friedman R, Mrazek P, Friesen B, Pires S, et al. Transforming mental health care for children and their families. Am Psychol 2005 Sep;60(6):615-627. [doi: 10.1037/0003-066X.60.6.615] [Medline: 16173894]
79. Hogan MF. The President's New Freedom Commission: recommendations to transform mental health care in America. Psychiatr Serv 2003 Nov;54(11):1467-1474. [doi: 10.1176/appi.ps.54.11.1467] [Medline: 14600303]
80. Singla DR, Kumbakumba E, Aboud FE. Effects of a parenting intervention to address maternal psychological wellbeing and child development and growth in rural Uganda: a community-based, cluster randomised trial. Lancet Glob Health 2015 Aug;3(8):e458-e469 [FREE Full text] [doi: 10.1016/S2214-109X(15)00099-6] [Medline: 26144389]
81. Manandhar DS, Osrin D, Shrestha BP, Mesko N, Morrison J, Tumbahangphe KM, Members of the MIRA Makwanpur trial team. Effect of a participatory intervention with women's groups on birth outcomes in Nepal: cluster-randomised controlled trial. Lancet 2004;364(9438):970-979. [doi: 10.1016/S0140-6736(04)17021-9] [Medline: 15364188]
82. Balaji M, Andrews T, Andrew G, Patel V. The acceptability, feasibility, and effectiveness of a population-based intervention to promote youth health: an exploratory study in Goa, India. J Adolesc Health 2011 May;48(5):453-460 [FREE Full text] [doi: 10.1016/j.jadohealth.2010.07.029] [Medline: 21501803]
83. Tripathy, Nair N, Barnett S, Mahapatra R, Borghi J, Rath S, et al. Effect of a participatory intervention with women's groups on birth outcomes and maternal depression in Jharkhand and Orissa, India: a cluster-randomised controlled trial. Lancet 2010 Apr 3;375(9721):1182-1192 [FREE Full text] [doi: 10.1016/S0140-6736(09)62042-0] [Medline: 20207411]
84. Jordans MJ, Aldridge L, Luitel NP, Baingana F, Kohrt BA. Evaluation of outcomes for psychosis and epilepsy treatment delivered by primary health care workers in Nepal: a cohort study. Int J Ment Health Syst 2017;11:70 [FREE Full text] [doi: 10.1186/s13033-017-0177-8] [Medline: 29204183]
85. Kohrt B, Asher L, Bhardwaj A, Fazel M, Jordans M, Mutamba B, et al. The role of communities in mental health care in low- and middle-income countries: a meta-review of components and competencies. Int J Environ Res Public Health 2018 Jun 16;15(6):pii: E1279 [FREE Full text] [doi: 10.3390/ijerph15061279] [Medline: 29914185]

86. Arnold I. Workplace Strategies for Mental Health. 2005. Peer Support Programs URL: https://www.workplacestrategiesformentalhealth.com/job-specific-strategies/peer-support-programs [accessed 2020-02-29]
87. Bartels SJ, DiMilia PR, Fortuna KL, Naslund JA. Integrated care for older adults with serious mental illness and medical comorbidity: evidence-based models and future research directions. Psychiatr Clin North Am 2018 Mar;41(1):153-164 [FREE Full text] [doi: 10.1016/j.psc.2017.10.012] [Medline: 29412843]
88. Bates A, Kemp V, Isaac M. Peer support shows promise in helping persons living with mental illness address their physical health needs. Can J Commun Ment Health 2008;27(2):21-36. [doi: 10.7870/cjcmh-2008-0015]
89. Hardy S, Hallett N, Chaplin E. Evaluating a peer support model of community wellbeing for mental health: a coproduction approach to evaluation. Ment Health Prev 2019;13(7):149-158 [FREE Full text] [doi: 10.1016/j.mhp.2019.01.007]
90. Cabassa LJ, Stefancic A, O'Hara K, El-Bassel N, Lewis-Fernández R, Luchsinger JA, et al. Peer-led healthy lifestyle program in supportive housing: study protocol for a randomized controlled trial. Trials 2015 Sep 2;16:388 [FREE Full text] [doi: 10.1186/s13063-015-0902-z] [Medline: 26329472]
91. Repper J, Carter T. A review of the literature on peer support in mental health services. J Ment Health 2011 Aug;20(4):392-411. [doi: 10.3109/09638237.2011.583947] [Medline: 21770786]
92. Fisher EB, Coufal MM, Parada H, Robinette JB, Tang PY, Urlaub DM, et al. Peer support in health care and prevention: cultural, organizational, and dissemination issues. Annu Rev Public Health 2014;35:363-383. [doi: 10.1146/annurev-publhealth-032013-182450] [Medline: 24387085]
93. MacLellan J, Surey J, Abubakar I, Stagg HR. Peer support workers in health: a qualitative metasynthesis of their experiences. PLoS One 2015;10(10):e0141122 [FREE Full text] [doi: 10.1371/journal.pone.0141122] [Medline: 26516780]
94. Fisher EB, Boothroyd RI, Coufal MM, Baumann LC, Mbanya JC, Rotheram-Borus MJ, et al. Peer support for self-management of diabetes improved outcomes in international settings. Health Aff (Millwood) 2012 Jan;31(1):130-139 [FREE Full text] [doi: 10.1377/hlthaff.2011.0914] [Medline: 22232103]
95. Singh P, Chokshi DA. Community health workers--a local solution to a global problem. N Engl J Med 2013 Sep 5;369(10):894-896. [doi: 10.1056/NEJMp1305636] [Medline: 24004115]
96. Kangovi S, Long JA, Emanuel E. Community health workers combat readmission. Arch Intern Med 2012 Dec 10;172(22):1756-1757. [doi: 10.1001/2013.jamainternmed.82] [Medline: 23128914]
97. Fisher EB, Ayala GX, Ibarra L, Cherrington AL, Elder JP, Tang TS, Peers for Progress Investigator Group. Contributions of peer support to health, health care, and prevention: papers from peers for progress. Ann Fam Med 2015 Aug;13(Suppl 1):S2-S8 [FREE Full text] [doi: 10.1370/afm.1852] [Medline: 26304968]
98. Tondora J, O'Connell M, Miller R, Dinzeo T, Bellamy C, Andres-Hyman R, et al. A clinical trial of peer-based culturally responsive person-centered care for psychosis for African Americans and Latinos. Clin Trials 2010 Aug;7(4):368-379 [FREE Full text] [doi: 10.1177/1740774510369847] [Medline: 20571133]
99. Sweeney A, Fahmy S, Nolan F, Morant N, Fox Z, Lloyd-Evans B, et al. The relationship between therapeutic alliance and service user satisfaction in mental health inpatient wards and crisis house alternatives: a cross-sectional study. PLoS One 2014;9(7):e100153 [FREE Full text] [doi: 10.1371/journal.pone.0100153] [Medline: 25010773]
100. Mancini MA. An exploration of factors that effect the implementation of peer support services in community mental health settings. Community Ment Health J 2018 Feb;54(2):127-137. [doi: 10.1007/s10597-017-0145-4] [Medline: 28466237]
101. Ahmed AO, Hunter KM, Mabe AP, Tucker SJ, Buckley PF. The professional experiences of peer specialists in the Georgia Mental Health Consumer Network. Community Ment Health J 2015 May;51(4):424-436. [doi: 10.1007/s10597-015-9854-8] [Medline: 25724917]
102. Walker G, Bryant W. Peer support in adult mental health services: a metasynthesis of qualitative findings. Psychiatr Rehabil J 2013 Mar;36(1):28-34. [doi: 10.1037/h0094744] [Medline: 23477647]
103. Villani M, Kovess-Masféty V. [Peer support programs in mental health in France: Status report and challenges]. Encephale 2018 Nov;44(5):457-464. [doi: 10.1016/j.encep.2018.01.003] [Medline: 29580700]
104. Cronise R, Teixeira C, Rogers ES, Harrington S. The peer support workforce: results of a national survey. Psychiatr Rehabil J 2016 Sep;39(3):211-221. [doi: 10.1037/prj0000222] [Medline: 27618458]
105. Corrigan PW, Kosyluk KA, Rüsch N. Reducing self-stigma by coming out proud. Am J Public Health 2013 May;103(5):794-800. [doi: 10.2105/AJPH.2012.301037] [Medline: 23488488]
106. Davis JK. Predictors of job satisfaction among peer providers on professional treatment teams in community-based agencies. Psychiatr Serv 2013 Feb 1;64(2):181-184. [doi: 10.1176/appi.ps.001452012] [Medline: 23370625]
107. Clossey L, Solomon P, Hu C, Gillen J, Zinn M. Predicting job satisfaction of mental health peer support workers (PSWs). Soc Work Ment Health 2018;16(6):682-695. [doi: 10.1080/15332985.2018.1483463]
108. Kemp V, Henderson AR. Challenges faced by mental health peer support workers: peer support from the peer supporter's point of view. Psychiatr Rehabil J 2012;35(4):337-340. [doi: 10.2975/35.4.2012.337.340] [Medline: 22491374]
109. Greer AM, Amlani A, Burmeister C, Scott A, Newman C, Lampkin H, et al. Peer engagement barriers and enablers: insights from people who use drugs in British Columbia, Canada. Can J Public Health 2019 Apr;110(2):227-235 [FREE Full text] [doi: 10.17269/s41997-018-0167-x] [Medline: 30610564]
110. Clossey L, Gillen J, Frankel H, Hernandez J. The experience of certified peer specialists in mental health. Soc Work Ment Health 2015;14(4):408-427. [doi: 10.1080/15332985.2015.1038412]

111. Vandewalle J, Debyser B, Beeckman D, Vandecasteele T, Van Hecke A, Verhaeghe S. Peer workers' perceptions and experiences of barriers to implementation of peer worker roles in mental health services: A literature review. Int J Nurs Stud 2016 Aug;60:234-250. [doi: 10.1016/j.ijnurstu.2016.04.018] [Medline: 27297384]
112. Gowen K, Deschaine M, Gruttadara D, Markey D. Young adults with mental health conditions and social networking websites: seeking tools to build community. Psychiatr Rehabil J 2012;35(3):245-250. [doi: 10.2975/35.3.2012.245.250] [Medline: 22246123]
113. Miller BJ, Stewart A, Schrimsher J, Peeples D, Buckley PF. How connected are people with schizophrenia? Cell phone, computer, email, and social media use. Psychiatry Res 2015 Feb 28;225(3):458-463. [doi: 10.1016/j.psychres.2014.11.067] [Medline: 25563669]
114. Naslund JA, Grande SW, Aschbrenner KA, Elwyn G. Naturally occurring peer support through social media: the experiences of individuals with severe mental illness using YouTube. PLoS One 2014;9(10):e110171 [FREE Full text] [doi: 10.1371/journal.pone.0110171] [Medline: 25333470]
115. Perry BL, Pescosolido BA. Social network activation: the role of health discussion partners in recovery from mental illness. Soc Sci Med 2015 Jan;125:116-128 [FREE Full text] [doi: 10.1016/j.socscimed.2013.12.033] [Medline: 24525260]
116. Chyzzy B, Dennis C. 16. Mobile phone-based peer support in the prevention of postpartum depression among adolescent mothers: a pilot randomized controlled trial. J Adolesc Health 2019;64(2):S8-S9. [doi: 10.1016/j.jadohealth.2018.10.030]
117. Urichuk L, Hrabok M, Hay K, Spurvey P, Sosdjan D, Knox M, et al. Enhancing peer support experience for patients discharged from acute psychiatric care: protocol for a randomised controlled pilot trial. BMJ Open 2018 Aug 17;8(8):e022433 [FREE Full text] [doi: 10.1136/bmjopen-2018-022433] [Medline: 30121611]
118. Hurley J, Cashin A, Mills J, Hutchinson M, Graham I. A critical discussion of Peer Workers: implications for the mental health nursing workforce. J Psychiatr Ment Health Nurs 2016 Mar;23(2):129-135. [doi: 10.1111/jpm.12286] [Medline: 26914867]
119. Burke EM, Pyle M, Machin K, Morrison AP. Providing mental health peer support 1: A Delphi study to develop consensus on the essential components, costs, benefits, barriers and facilitators. Int J Soc Psychiatry 2018;64(8):799-812. [doi: 10.1177/0020764018810299]
120. Agyapong VI, Juhás M, Mrklas K, Hrabok M, Omeje J, Gladue I, et al. Randomized controlled pilot trial of supportive text messaging for alcohol use disorder patients. J Subst Abuse Treat 2018 Nov;94:74-80. [doi: 10.1016/j.jsat.2018.08.014] [Medline: 30243421]
121. Agyapong VI, Ahern S, McLoughlin DM, Farren CK. Supportive text messaging for depression and comorbid alcohol use disorder: single-blind randomised trial. J Affect Disord 2012 Dec 10;141(2-3):168-176. [doi: 10.1016/j.jad.2012.02.040] [Medline: 22464008]
122. Gill K. New Moves: Targeting physical and mental illness well-being in people with mental illness. Health Issues J 2012;108(1):18-23 [FREE Full text] [doi: 10.13140/2.1.3918.1447]
123. Martin M, Martin SL. Healthy Amistad: improving the health of people with severe mental illness. Issues Ment Health Nurs 2014 Oct;35(10):791-795. [doi: 10.3109/01612840.2014.915898] [Medline: 25259642]
124. Lorig K, Ritter PL, Pifer C, Werner P. Effectiveness of the chronic disease self-management program for persons with a serious mental illness: a translation study. Community Ment Health J 2014 Jan;50(1):96-103. [doi: 10.1007/s10597-013-9615-5] [Medline: 23748554]
125. Bouchard L, Montreuil M, Gros C. Peer support among inpatients in an adult mental health setting. Issues Ment Health Nurs 2010 Sep;31(9):589-598. [doi: 10.3109/01612841003793049] [Medline: 20701422]
126. Hurley J, Cashin A, Mills J, Hutchinson M, Kozlowski D, Graham I. Qualitative study of peer workers within the 'Partners in Recovery' programme in regional Australia. Int J Ment Health Nurs 2018 Feb;27(1):187-195. [doi: 10.1111/inm.12308] [Medline: 28000980]
127. Simmons D, Bunn C, Nakwagala F, Safford MM, Ayala GX, Riddell M, et al. Challenges in the ethical review of peer support interventions. Ann Fam Med 2015 Aug;13(Suppl 1):S79-S86 [FREE Full text] [doi: 10.1370/afm.1803] [Medline: 26304976]

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## Abbreviations

**CRPD:** Convention on the Rights of Persons with Disabilities
**EPSS:** Edmonton peer support system
**IPS:** intentional peer support
**PSS:** peer support service
**PSW:** peer support worker
**PWD:** people with disability
**QOL:** quality of life
**RCT:** randomized controlled trial
**SAMHSA:** Substance Abuse and Mental Health Services Administration
**SMI:** serious mental illness

**TIC:** trauma-informed care

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Original Paper

# Engaging With a Web-Based Psychosocial Intervention for Psychosis: Qualitative Study of User Experiences

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## Abstract

**Background:** Web-based interventions are increasingly being used for individuals with serious mental illness, including psychosis, and preliminary evidence suggests clinical benefits. To achieve such benefits, individuals must have some level of engagement with the intervention. Currently, little is known about what influences engagement with web-based interventions for individuals with psychotic disorders.

**Objective:** This study aimed to explore users' perspectives on what influenced engagement with a web-based intervention for psychosis.

**Methods:** A qualitative design was employed using semistructured telephone interviews. Participants were 17 adults with psychosis who had participated in a trial examining engagement with a self-guided, web-based intervention promoting personal recovery and self-management of mental health.

**Results:** We identified 2 overarching themes: *challenges to using the website* and *factors supporting persistence*. Both of the main themes included several subthemes related to both user-related factors (eg, mental health, personal circumstances, approach to using the website) and users' experience of the intervention (eg, having experienced similar content previously or finding the material confronting).

**Conclusions:** Individuals with psychosis experienced several challenges to ongoing engagement with a web-based intervention. Adjunctive emails present an important design feature to maintain interest and motivation to engage with the intervention. However, fluctuations in mental health and psychosocial difficulties are a significant challenge. Design and implementation considerations include flexible interventions with tailoring opportunities to accommodate changeable circumstances and individual preferences.

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**KEYWORDS**

psychosis; engagement; qualitative research; eHealth; internet intervention; mobile phone

## Introduction

### Background

Access to the internet and digital technologies is increasing among individuals with psychosis [1,2]. Many individuals with psychosis are active and proficient users of technology and the internet [3-5] and demonstrate positive attitudes toward using digital technologies to support mental health and self-management [6,7]. This increased access and interest provide a unique opportunity to promote self-management of mental health via internet- and mobile-based interventions. To meet this opportunity, several mobile apps and internet-based interventions have been developed to promote self-management of mental health in psychosis [8-11]. Both internet- and mobile-based interventions (hereafter named *web-based interventions*) appear feasible, acceptable, and potentially effective in improving clinical outcomes for individuals with psychotic disorders [12-15].

Despite potential benefits, engagement with web-based interventions for psychosis may be variable [16]. Some individuals may be very engaged and high users of an intervention. However, a large proportion will have only initial or infrequent use of an intervention, thus limiting potential associated benefits [17]. Individuals with psychotic disorders may have specific difficulties related to engaging with web-based interventions. For example, cognitive deficits, reduced awareness of illness, and positive and negative symptoms may present as challenges to using the internet and web-based interventions [4,18]. Additionally, some individuals with psychosis may have limited computer literacy and additional barriers to internet use and access. These barriers are potentially associated with less educational and vocational attainment or the impact of symptoms [2,4,19].

Qualitative methods can enable the exploration of user experiences and reveal factors that support or obstruct engagement with web-based interventions [20]. The investigation into web-based interventions for broader mental health difficulties has highlighted various factors that impede or support engagement with web-based interventions. Previously identified challenges to engagement include mental health symptoms (such as low mood, anxiety, and mania), current life situation (such as competing demands), and negative perceptions or experiences of the intervention (eg, perceived poor fit with the user) [21-25]. Conversely, positive intervention experiences (such as a sense of autonomy, competence, or connection) and finding an intervention beneficial have previously been reported as facilitators of engagement with web-based interventions [21,26,27].

Previous research has qualitatively investigated users' experiences of web-based interventions for psychosis [28-30]. However, these studies have largely focused on broader perceptions and evaluations of relevant interventions, such as acceptability and associated impacts. To date, limited research has specifically examined how people with psychosis engage with web-based interventions or factors that may influence engagement. Eisner and colleagues [10] recently investigated barriers to engagement with a mobile app for symptom monitoring in schizophrenia (the Experiences of Psychosis Relapse: Early Subjective Signs app). Participants who used the app over 6 months identified both mental health and phone-related barriers to engagement with the app. Some participants reported positive symptoms impacted concentration, which made answering questions on the app more strenuous. Others reported difficulties using smartphones because of a lack of experience.

### Objectives

Web-based–self-management programs are another type of digital intervention for which there is a lack of research examining user experiences of engagement. This study aimed to explore user experiences of engaging with a web-based program for psychosis and identify factors associated with engagement and disengagement.

## Methods

### Research Context

This qualitative study was embedded in a broader research project that examined predictors of engagement with a web-based intervention for individuals with psychosis—the Self-Management and Recovery Technology (SMART) website [16]. The broader research program involved a trial on the use of the website on a tablet computer in face-to-face sessions to examine efficacy [31,32] and examining integration into routine mental health services. This study formed part of an investigation into the potential to use the SMART website as a predominantly self-guided, low-intensity, web-based intervention [16].

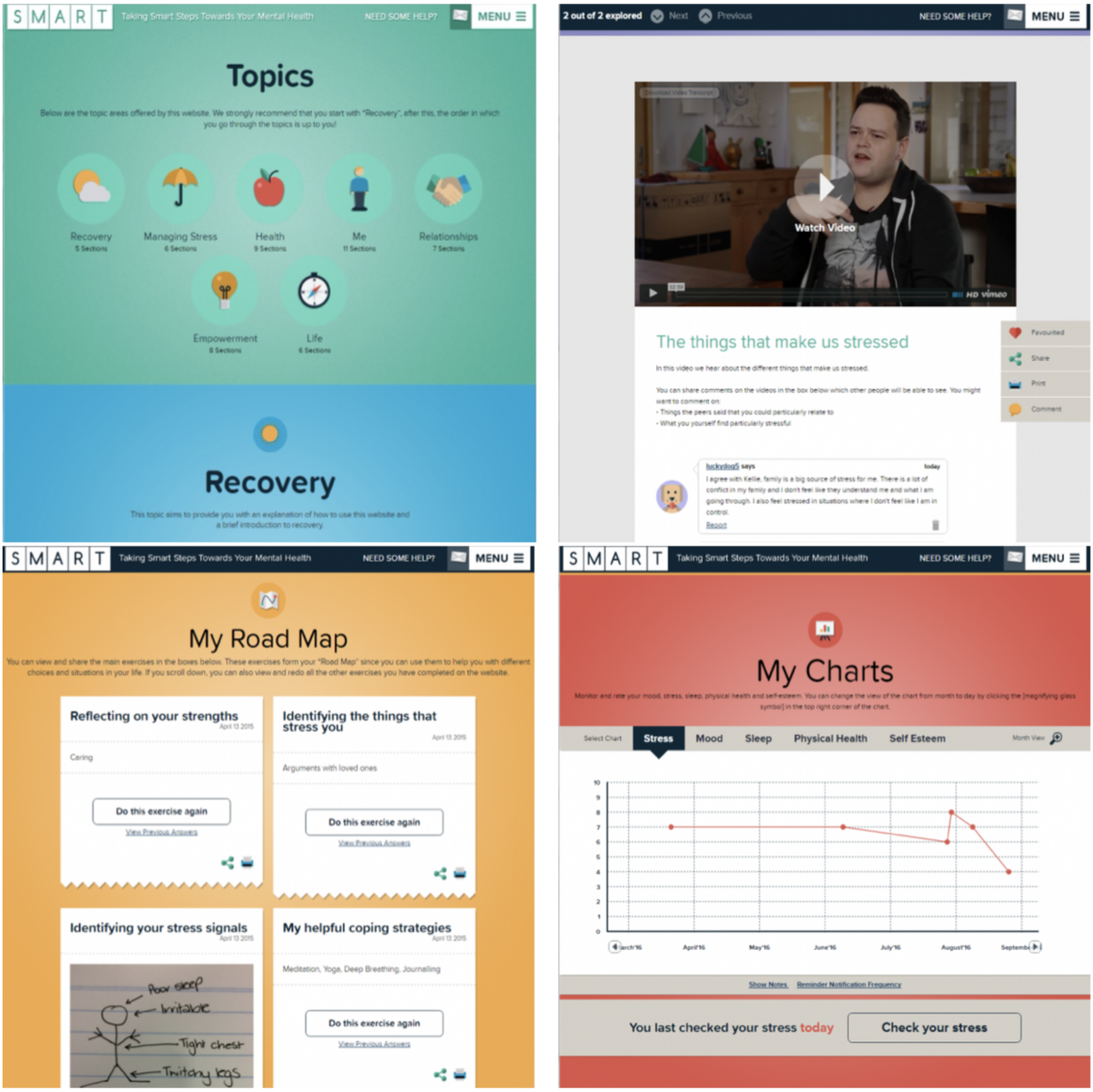
The website aimed to promote self-management of mental health and personal recovery (ie, living a meaningful and satisfying life despite potential difficulties associated with experiences of mental illness) in people with psychotic disorders [31,33]. Website content was organized into 7 modules on recovery, stress management, relationships, health, values, empowerment, and stigma and identity. Each module contained video-based content of peers with lived experience of psychosis, discussing their personal experiences and opinions of the particular topic and associated activities. Additional website features included charting tools (eg, to track stress, sleep, etc) and social networking features, including a peer-moderated forum (Figure 1 shows example screenshots).

The website was designed in accordance with guidelines for individuals with serious mental illness and cognitive deficits [34]. This included simplification of navigation and content and minimization of text where possible [31]. Website development involved a co-design process with consumers and mental health workers who indicated a preference for an intervention that could be used flexibly rather than sequentially. Additionally, as this resource focused on personal recovery, a highly individualized process [35], the website was designed as a resource of web-based materials that could be used flexibly. The *Recovery* module included information on how to use the website and was the recommended but optional starting point. Otherwise, the website did not have a specified order or end point and could be used in accordance with users' personal preferences. A full description of the SMART website is detailed elsewhere [31].

A total of 98 participants were recruited from across Australia and given access to the website for ≥12 weeks. The website automatically randomized participants on a 1:1 basis to receive either (1) access to the website only or (2) access to the website in conjunction with weekly, asynchronous, support emails from a mental health worker at a project partner for 12 weeks. Support emails did not aim to be therapeutic but encouraged users to work through website material [16].

All participants completed research-related questionnaires before signing up to the website and received email reminders to complete follow-up questionnaires at 4 and 12 weeks postregistration. All participants could also select to receive additional system-automated reminder emails to complete activities on the website (eg, mood tracking). Participants used the website on their personal or otherwise internet-accessible devices. Users were advised to use the website as they chose in accordance with personal interests and preferences.

**Figure 1.** Example screenshots from the Self-Management and Recovery Technology website.



## Research Design

We employed an exploratory qualitative study using an inductive approach [36]. Semistructured interviews were used to enable a more in-depth discussion of experiences and provide opportunities to explore and clarify participant responses [37,38]. We used a semantic approach to theme development within an essentialist/realist paradigm aimed at objectively capturing the lived experience of participants [36,39].

## Participant Recruitment

Participants were drawn from the primary study [16]. The original inclusion criteria were the following: (1) aged between 18 and 65 years inclusive, (2) currently residing in Australia, (3) diagnosis of a nonorganic psychotic disorder (schizophrenia-related disorder, bipolar disorder, or major depressive disorder with psychotic features present within the past 2 years) confirmed using the Structured Clinical Interview for Diagnostic and Statistical Manual of Mental Disorders, fourth edition,-text revision Axis I Disorders [40], (5) proficiency in the English language, and (6) willingness to access and use the internet. Exclusion criteria included experiences of psychosis only during substance intoxication and no internet access.

Following the 12-week intervention period, participants were contacted via email by the first author (CA) and invited to participate in the interview. To minimize recall issues without impacting participants' use of the website for the primary study, we aimed to conduct interviews as close as possible to the intervention end date. Initially, a pool of consecutive participants was invited to participate. After initial interviews, we purposefully selected participants with the goal of ensuring diversity of age, gender, condition (with and without adjunct email support), and use of the website (from no use to long-term, high use). We recruited participants until saturation occurred, and no new information arose from interviews. Participants were reimbursed with an AUD $30 (US $19.3) gift card for completing the interview. Some participants were previously assessed for eligibility for the main study by the interviewer (CA). Otherwise, there was no existing relationship between the interviewer and participants.

### Data Collection

Data were collected via semistructured telephone interviews with 17 participants. The interviews followed a semistructured interview guide with open-ended questions about potential factors that may have influenced engagement with the website (Multimedia Appendix 1). A panel of individuals with lived experiences of psychosis provided feedback on the interview guide before data collection began. During data collection, additional questions were formulated and added to the interview schedule in an iterative process, depending on participant responses. The interview schedule thus evolved over the course of the study. Field notes were made following each interview, and interviews were transcribed verbatim from audio recordings. Transcription of one interview was not possible because of a recording error. On this occasion, attempts were made to outline the interview content as closely as possible from memory.

### Data Analysis

Data were analyzed using a thematic analysis approach [36]. Data collection and analyses occurred concurrently. The first author familiarized herself with the data by listening to and reading each interview multiple times with reference to field notes. The first author initially coded all interviews using an inductive approach. The second author (AW) also coded early interviews and subsequently discussed the first author's coding in the process of peer review. Following the completion of data collection and preliminary coding of all interviews, the first author recoded all data with new codes using NVivo 12 (QSR International) and then developed a coding framework. The coding framework was used to inform the development of categories and subsequent themes based on patterns identified in the codes. Developing categories and themes were discussed between the authors and refined in an iterative manner.

### Methodological Integrity

The authors were from clinical psychology (CA and NT) and occupational therapy (AW) professional backgrounds. The first author was familiar with the literature on engagement with web-based interventions among individuals with serious mental illness. Despite aiming to follow a data-driven approach, this knowledge may have influenced the interpretation of data. The first author's perspectives were managed by reflective note taking and discussion with other authors to ensure that the interpretations were aligned with the collected data and not based on pre-existing assumptions. The first author received training in qualitative research methods. The second and third authors additionally had experience using qualitative research methods with individuals with psychosis. A panel of individuals with lived experiences of psychosis provided feedback on the authors' understanding of data during thematic analysis and supported the interpretation. We followed the American Psychological Association reporting standards for qualitative research throughout this manuscript [41].

## Results

### Participant Details

A total of 17 participants were interviewed via telephone, with interviews lasting between 17 and 58 min (average time 30 min). There was a near equal distribution of participants who received access to the website only (n=8) and those who additionally received the support emails (n=9). Participants reported using the website on their smartphones, computers (desktops and laptops), tablet computers, and a combination of devices. Participants logged on to the website an average of 15 times (range 3-40) and completed an average of 62 activities on the website (range 6-316). Participant characteristics are outlined in Table 1.

**Table 1.** Participant characteristics (N=17).

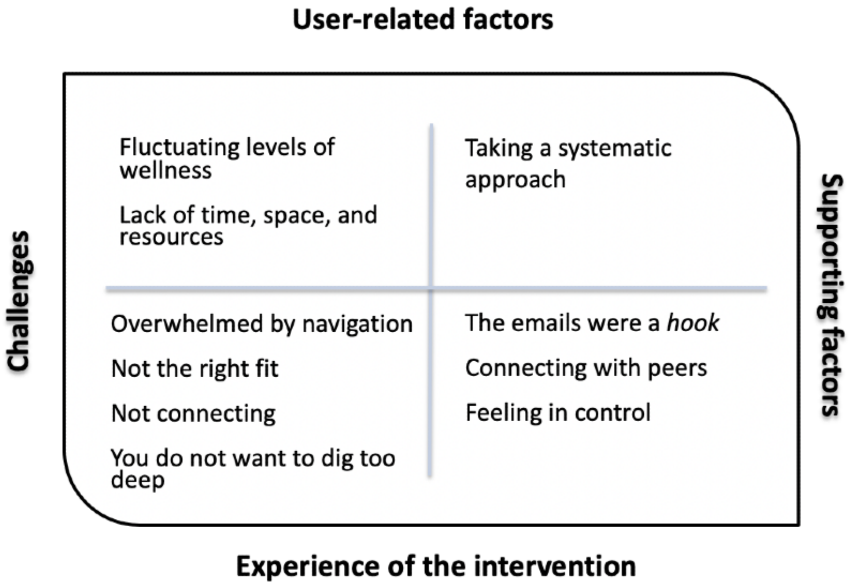
| Variable | Participants, n (%) |
|---|---|
| **Age (years)** | |
| 18-34 | 7 (41) |
| 35-50 | 6 (35) |
| 51-65 | 4 (24) |
| **Gender** | |
| Female | 11 (65) |
| Male | 6 (35) |
| **Level of education** | |
| Secondary school | 5 (29) |
| Apprenticeship or diploma or certificate | 4 (24) |
| Bachelor's degree | 5 (29) |
| Postgraduate degree | 3 (18) |
| **Recent employment status** | |
| Paid or self-employment | 4 (24) |
| Unemployed | 13 (76) |
| **SCID[a] diagnosis** | |
| Schizoaffective disorder | 5 (29) |
| Schizophrenia | 5 (29) |
| Bipolar disorder with psychotic features | 4 (24) |
| Major depression with psychotic features | 3 (18) |
| **Confidence using the internet** | |
| Confident without assistance | 15 (88) |
| Occasionally need assistance | 2 (12) |
| **Frequency of internet use** | |
| More than once a day | 16 (94) |
| A few times a week | 1 (6) |

[a] SCID: Structured Clinical Interview for Diagnostic and Statistical Manual of Mental Disorders, fourth edition, text revision Axis I Disorders.

## Salient Themes

We identified 2 central themes related to participants' engagement with the website: *challenges to using the website* and *factors supporting persistence*. Many participants spoke about initial interest and motivation to use the website and expected to use the resource more than they did. These participants identified significant challenges in engaging with the website. A smaller number of participants persisted with the intervention and reported a positive experience. They identified factors that supported them to sustain their engagement with the website. Each theme had subthemes relating to both user-related factors and users' experiences of the intervention. The main themes and subthemes are outlined in Figure 2 and further discussed in the following sections. Quotes from participants have been included to illustrate each finding. Participants' names have been replaced with a unique identifier to maintain participant anonymity.

**Figure 2.** Challenges to engagement and factors supporting persistence with the website.



## Challenges in Using the Website

### *User-Related Factors*

#### Fluctuating Levels of Wellness

Fluctuations in participants' mental health played an important role in their engagement with the website. A total of 9 participants reported mental health–related challenges to engagement. Participants referred to fluctuating levels of wellness that influenced their interest toward and the potential to engage with and gain meaning from using the website:

> *Because it's such a tidal wave of different mental states and sometimes normality, it really depends on the day… how you're feeling and how you can cope.* [P17, website only]

Participants spoke about motivation difficulties associated with psychosis and mood difficulties. During periods of low energy and motivation, the efforts of participants were focused on tasks of daily living. As such, anything *extra*, such as the website, was not a priority or deemed too burdensome to consider:

> *And it's really hard to get motivated to do anything. And that was sort of like the last thing, you know? Like getting up is hard enough. Let alone trying to [use the website].* [P14, email support]

Paranoid thoughts also impacted participants' willingness to engage with the website. A total of 3 participants reported fluctuating levels of suspiciousness toward technology and concerns about the privacy of the information on the web:

> *I personally don't feel comfortable typing any of the answers to any of these things into a website. Because, part of my paranoid thoughts is this feeling like, issues about privacy and technology. And it's just all too much for me to type.* [P10, website only]

A participant mentioned not using the website during a psychotic episode that she experienced when participating in the study. The participant reported that during periods of psychotic *relapse*, she did not use the intervention as she would have had difficulty processing the material on the website:

> *I guess I just can't really stand the screen and words get jumbled up and things like that… I wouldn't have been able to make sense of the topics…* [P7, website only]

This was seconded by another participant who highlighted the limited benefit of resources such as the website during a psychotic episode:

> *I know that this SMART online wouldn't have helped me then…. It's like you won't even come to the website. And, even if someone puts you in front of the website, it just would not mean anything.* [P11, website only]

Importantly, when the impact of symptoms decreased, some participants were able to re-engage with the website.

#### Lack of Time, Space, and Resources

Engagement with the SMART website was influenced by the personal circumstances of participants. A total of 7 participants reported struggling to find time to spend on the website or simply forgot:

> *Time was an important factor. I just didn't have the time that I'd like to spend on it. And, I couldn't get into it as thoroughly as I would have liked.* [P5, email support]

Overall, 5 participants experienced significant psychosocial stressors during their participation period, including periods of homelessness, physical health difficulties, and accidents. As highlighted by a participant, a period of homelessness meant that the website was not a priority for him:

> *… around late February my living situation changed drastically. And so, yeah, I no longer have the time or space to do it.* [P13, email support]

For 4 participants, gaining access to the website was also a practical barrier to engagement. Some participants did not have ready access to the internet because of financial limitations or homelessness, and others had limited data on their mobile phones. As the majority of participants had only 1 device available to them, this meant that participants did not have the means to access the website.

### *Experience of the Website*

Once a participant had accessed the website, their early experience of the website contributed to their decision making about continued engagement with the website or disengagement. In particular, whether or not participants persisted with using the website was influenced by experiencing difficulties navigating the site, a lack of connection with the content or users, and negative emotional experiences associated with use.

#### Overwhelmed by Navigation

Overall, 5 participants found it difficult to navigate the website. When experiencing this difficulty, some participants felt that using the website required too much effort or was overwhelming:

> *I saw that there was forums and stuff. And I wanted to go and do it, but then I just couldn't navigate it. And I was just like, "Oh, I can't be bothered."* [P14, email support]

For others, the lack of direction in how to use the website, in combination with the amount of content, was daunting and overwhelming:

> *It felt like because it's all listed there in sections and there's so many there that it felt like you try and start reading them you feel like you're having a bit of trouble getting through it. And then you think, "Oh well, I might as well just not bother trying to read all these, or watch all these, because it's all a bit much."* [P10, website only]

#### Not the Right Fit

Early experiences of the intervention influenced the interest participants had in persisting with the intervention. When participants had previously encountered similar material, or they deemed the website irrelevant to their immediate needs, their interest in continuing waned:

> *Either it wasn't relevant or it was stuff I'd sort of thought about previously already. So I didn't feel I needed to go over it again.* [P8, email support]

#### Not Connecting

A total of 8 participants reported signing up to the SMART website because they wanted to hear from, learn about, and share with individuals with similar experiences:

> *I was interested in the forums and to see what other people were saying about their experiences with mental health and hearing voices. And to see if there was any similarities with my experience and other people, and to kind of connect.* [P2, website only]

When participants sought connections with others but did not have this experience as part of using the website, their motivation to continue using aspects of the website, such as the forum or the videos, decreased:

> *To be honest, I haven't connected with anyone on the SMART website… Nothing has jumped out at me, and I haven't really gone in there and attempted to make contact… If I had to point to a negative, it would be the fact that it's not social, it's not socially enabled.* [P11, website only]

#### You Do Not Want to Dig Too Deep

Overall, 3 participants found some of the content of the website to be deflating, confronting, or triggering:

> *Depending on how you're feeling, it can be quite triggering… and it kind of makes you fear the reality of this is really how you're feeling. Yeah, it kind of puts it into reality what's there.* [P14, email support]

For these participants, this was an unpleasant reminder about their situation. They preferred not to think about their mental illness, as it was associated with difficult emotions, as highlighted by 2 participants as follows:

> *Well, it's interesting. When you have a mental illness you don't like to dig too deep too often because it's quite depressing…I try to keep my mental illness in my pocket, if you like.* [P17, website only]
>
> *My best, my best, days are when I typically forget, um, that I have any kind of illness. And I get to live life for a little while without remembering that it's an issue that I actually face. And I get caught up in just everyday things that everybody else gets caught up in. And things seem normal like they were before I was sick. So to be reminded, or to be very heavily reminded about the gravity of it all can be a bit, unpleasant.* [P10, website only]

These unpleasant emotions resulted in an urge to withdraw from the website:

> *But I feel like it's the kind of content that for some reason that feeling of stigma just kicks in you know every couple of minutes and you start to feel like, "Well maybe, well maybe I shouldn't do this."* [P10, website only]

## Factors Supporting Persistence

### *User-Related Factors*

#### Taking a Systematic Approach

The few participants who persisted with the intervention over the 12-week period came up with strategies that supported their continued use of the website. For example, a participant spoke about incorporating the SMART website into her weekly routine and a methodical approach to using the website:

> *I try to get on there on Saturdays… I basically go to a topic that I haven't completed and I try to complete the topic or I go to a new topic and I start with the videos. And then I go through the activities and fill in the activities.* [P7, website only]

Similarly, another participant who persisted with the website spoke about making her way through the website systematically:

> *I tried to do it systematically… I went through each section and first I did the main things not the extras. And then over time I did mark the extras and I got through most of the content.* [P4, email support]

## *Experience of the Website*

### The Emails Were a Hook

The majority of participants (n=15) reported finding the system-automated or support emails particularly helpful for the ongoing use of the website. As highlighted by the following participant, receiving the emails reminded participants about the website and prompted them to re-engage with the resource:

> *Having the prompts all the time like the emails was really good, because it sort of made me think, "Oh, you know, I should jump on and have a look and see if there's anything that I can find that might help me stay positive and keep my mental health going well while I'm sick."* [P16, email support]

Additionally, the support emails from the web-based therapist served as an incentive for some participants to persist with the website. They not only reminded participants about the website but also made individuals interested in returning to the website and more invested in using the resource:

> *… I knew that [the web-based therapist] would be responsive no matter what I said. So, it kind of made me look forward to those email and sign back on to the website. It was like a hook.* [P4, email support]

Some participants felt a sense of connection with their web-based therapist. When individuals felt supported by their therapist, it facilitated connection and made participants more open to using the website:

> *It sort of made it feel a little more personalised, made me more open to accessing the service. Knowing that there was a real person… on the other end made a fair difference.* [P13, email support]

### Connecting With Peers

Overall, 5 participants resonated with the experiences of their peers in the videos, or with other users on the forum. For those who did connect with the experiences of others, this shaped their experience of the website into a positive one. For some users, this connection facilitated the ongoing use of the website:

> *It was really interesting to me. I really liked getting to know the different interviewees and following them through the different topics…I just was so motivated to see the videos. It's like meeting new people in the videos.* [P7, website only]

### Feeling in Control

A few participants (n=4) reported a strong appreciation for the flexibility of the intervention. They felt in control of their use of the resource. This was a change from previous experiences and resulted in a positive view of the resource. They reported appreciating this flexibility and even engaging more broadly as a result:

> *It was a lot more flexible than things I've dealt with in the past. I think I just looked into more things because they were readily available…. Yeah, it was never a case of it's either this way or the highway, it was a case of well, if this isn't great for you then try something else.* [P3, email support]

# Discussion

### Principal Findings

This study explored the experience of individuals with psychosis engaging with a web-based psychosocial intervention with and without adjunct email support. Participants who initially evaluated the website as novel and/or relevant to them, intended to continue using the website. Those who persisted with the website used strategies to support use and worked through website content systematically. Both the reminder and support emails were helpful factors in persisting or re-engaging with the resource for many participants. Other participants intended to persist with the intervention, but mental health difficulties, psychosocial stressors, and limited access served as barriers to engagement. Feeling overwhelmed when navigating the website or feeling dejected by the content deterred participants from engaging with the website. When participants initially evaluated the resource as being irrelevant or not useful, there was also limited interest in persisting with the resource.

### Leveraging Supportive Factors

In this study, receiving email support was a key facilitator of engagement. This is consistent with findings from the primary study, where individuals receiving adjunct email support were significantly more engaged than participants accessing the website only [16]. The qualitative findings assist in explaining this difference. As with previous research, participants who did not receive email support found that their motivation to persist with the intervention waned quickly [23,42]. In contrast, receiving support emails made participants more open to using the website and maintained interest and persistence over time. Some participants felt accountable to their email support person, suggesting that emails served as an effective external motivating factor to engage [43].

In addition to the support emails sent by the mental health worker, automated emails were also perceived as helpful. The automated emails reminded participants about the website and enabled re-engagement with the resource following periods of nonuse. This is consistent with the previous investigation, where automated emails increased adherence with self-guided interventions, and reminders have been regarded as especially helpful [44,45]. Personalized support emails appear optimal as they can promote motivation to engage and explore resources. However, periodic automated reminders may be a cost-effective approach to remind users about the intervention and promote engagement.

Users who persisted with the website resonated with the content and connected with their peers in the videos or other website users. In contrast, participants had limited motivation to persist with the resource when it was perceived as irrelevant or nothing new. Relatedness (ie, recognition and connection) is considered an important factor in promoting intrinsic motivation to engage with interventions [46]. Community, connection, and support opportunities have largely been experienced as positive components of web-based interventions [44,47]. Our findings support the importance of relatedness and the inclusion of social opportunities in intervention design. Additionally, tailoring interventions to accommodate varying interests may be helpful to ensure that interventions are relevant and accordingly promote motivation and engagement [48,49].

The results of this study and previous research suggest that a sense of control is likely to promote engagement with web-based interventions [21,27]. Interventions may therefore seek to incorporate ways to promote autonomy throughout [27]. This could include, for example, options for self-tailoring and options for choice [50]. This may be especially important for individuals with psychosis who may have had negative and disempowering mental health–related experiences, such as involuntary treatment [51].

Finally, individuals who persisted with the intervention used various strategies to support their use of the intervention. Incorporating goal setting to support the implementation of the website into the lives of users may therefore be a helpful component to promote engagement [52].

### Overcoming Challenges

Consistent with reports from other diagnostic groups, mental health appears to be an important factor in engagement with web-based interventions for psychosis [24,25]. Participants with and without adjunct email support reported that fluctuations in mental health impacted engagement. Individuals with psychosis have previously reported reduced internet use when unwell because of motivational and comprehension difficulties [53]. Concurrently, some participants in this study reported low mood and energy decreased motivation to engage with the website. Other participants reported suspiciousness toward the intervention, which resulted in nonuse. Additionally, participants regarded web-based interventions as having limited potential utility during episodes of psychosis. These results support a recent finding that mental health symptoms interfere with user engagement with a mobile monitoring app for psychosis [10]. Importantly, when the impact of symptoms decreased, some participants re-engaged with the website following receipt of reminder emails.

Participants reported difficulties in finding time to use the website. This has been identified as a challenge in previous studies of web-based interventions for other mental health difficulties such as depression, anxiety, and bipolar disorder [21,42,54]. Several participants in this study also faced significant psychosocial stressors such as homelessness during the period of participation. This has not commonly been reported among other diagnostic groups and suggests that this may be a unique challenge for some individuals with psychosis. During periods of acute psychosis or crisis, needs and priorities may shift from long-term recovery goals to one's immediate situation and safety [55]. Although email support generally promoted engagement in this study, it did not appear to overcome serious mental health or psychosocial difficulties. Rather than advocating for continued engagement, web-based interventions may need to enable flexible use over time, depending on current needs and circumstances. A flexible resource that can accommodate periods of nonuse and allow for re-engagement when circumstances and mental health permits may, therefore, be optimal.

Individuals with psychosis and broader mental health difficulties have reported challenges in using the internet and web-based interventions because of low levels of computer skills and confidence [10,26,53]. Despite attempts to simplify website design and content, some participants in this study experienced difficulty navigating the website and found this process overwhelming. This finding supports the design of interventions that are simple, intuitive, and easy to use to accommodate potential lower levels of computer literacy [56]. A co-design process with both consumers and human-computer experts may serve to improve the design and usability of web-based interventions [50,57]. More on-demand technical support or initial training in how to use an intervention may be helpful to overcome this difficulty [18,58].

Some participants found website content confronting and upsetting, which discouraged them from persisting. This mirrors reports from individuals with bipolar disorder who disengaged from a previous web-based psychoeducation program because of experiencing the intervention as confronting, overwhelming, and deflating [24]. Participants' experiences may potentially reflect a *sealing over* recovery style, whereby individuals attempt to alleviate distress through avoidance-based coping strategies [59]. Individuals with a sealing over recovery style typically prefer not to think about their experiences of psychosis and avoid talking about their experiences [60]. Congruently, participants who found the website content confronting reported preferring not to think about their mental illness and avoiding engaging with material on this topic. A potential sealing over recovery style was also identified as a reason for wanting to discontinue using the mobile monitoring app in a recent study by Eisner et al [10].

Although these experiences appear consistent with a sealing over approach, the recovery style of participants did not predict engagement with the website in the primary study [16]. This discrepancy may be the result of the modest reliability of the scale used within the primary study, the low number of participants endorsing a strong sealing over recovery style, or misinterpretation of participants' experiences. As such, further mixed methods research specifically investigating the potential association between recovery style and engagement with web-based interventions among individuals with psychosis is warranted. Regardless of whether these experiences represent a sealing over recovery style, some participants found website content distressing, which resulted in avoidance. Potentially more individualized or in-person support may be required to work through this type of recovery-focused material for some individuals with psychosis.

### Strengths and Limitations

Previous qualitative research has investigated the acceptability and feasibility of using digital technologies for mental health–related purposes [6,53]. However, there has been limited exploration of user perspectives on factors that influence engagement with web-based resources. This study identified several factors that can inform the design and implementation of future web-based interventions. This study may serve as a useful starting point for future research to further investigate processes associated with engagement and outcome in web-based interventions for psychosis. A key strength of this study was the examination of actual, rather than hypothetical, user experiences of the intervention [13]. Methodological integrity was preserved through reflective practice, consultation with other academics, and member checking of results via consultation with individuals with lived experience of psychosis.

We aimed to conduct interviews with participants as soon as possible following the 12-week intervention period. However, as some participants only used the website once or a few times, several weeks had passed between final use and the interview. The interviews were conducted via telephone, which may have potentially limited the richness of collected data [61,62]. Additionally, although we aimed to examine engagement with the website in a naturalistic manner, there may have been unintended effects of the research context that may impact the results [26]. Participants had all agreed to participate in a study involving the use of a web-based intervention and may represent a subgroup of individuals with psychosis who have more interest in digital mental health. In this study, the majority of participants were confident and frequent users of the internet. However, our sample was otherwise sufficiently diverse with regard to gender, age, and level of intervention use.

## Conclusions

Individuals with psychosis experienced several challenges to engagement with a self-guided web-based intervention. In addition to mental health–related problems, psychosocial stressors and navigation issues presented as difficulties engaging with the intervention. Web-based interventions may need to be flexible to accommodate changeable circumstances. The provision of email support may serve as a successful reminder to use an intervention, encourage exploration of intervention aspects, and maintain motivation. Tailoring the intervention to the user's interests and preferences appears to be important to promote engagement. Further research is required to investigate the relationship between engagement and clinical benefits among individuals with psychosis.

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## Conflicts of Interest

None declared.

Multimedia Appendix 1
Qualitative interview guide.
[DOCX File , 16 KB - mental_v7i6e16730_app1.docx ]

## References

1. Gay K, Torous J, Joseph A, Pandya A, Duckworth K. Digital technology use among individuals with schizophrenia: results of an online survey. JMIR Ment Health 2016 May 4;3(2):e15 [FREE Full text] [doi: 10.2196/mental.5379] [Medline: 27146094]
2. Robotham D, Satkunanathan S, Doughty L, Wykes T. Do we still have a digital divide in mental health? A five-year survey follow-up. J Med Internet Res 2016 Nov 22;18(11):e309 [FREE Full text] [doi: 10.2196/jmir.6511] [Medline: 27876684]
3. Fernández-Sotos P, Fernández-Caballero A, González P, Aparicio AI, Martínez-Gras I, Torio I, et al. Digital technology for internet access by patients with early-stage schizophrenia in Spain: multicenter research study. J Med Internet Res 2019 Mar 14;21(4):e11824 [FREE Full text] [doi: 10.2196/11824] [Medline: 30950798]
4. Villagonzalo K, Arnold C, Farhall J, Rossell SL, Foley F, Thomas N. Predictors of overall and mental health-related internet use in adults with psychosis. Psychiatry Res 2019 Aug;278:12-18. [doi: 10.1016/j.psychres.2019.05.034] [Medline: 31132571]
5. Thomas N, Foley F, Lindblom K, Lee S. Are people with severe mental illness ready for online interventions? Access and use of the internet in Australian mental health service users. Australas Psychiatry 2017 Jun;25(3):257-261. [doi: 10.1177/1039856217689913] [Medline: 28139947]
6. Bucci S, Morris R, Berry K, Berry N, Haddock G, Barrowclough C, et al. Early psychosis service user views on digital technology: qualitative analysis. JMIR Ment Health 2018 Oct 31;5(4):e10091 [FREE Full text] [doi: 10.2196/10091] [Medline: 30381280]
7. Firth J, Cotter J, Torous J, Bucci S, Firth JA, Yung AR. Mobile phone ownership and endorsement of 'mhealth' among people with psychosis: a meta-analysis of cross-sectional studies. Schizophr Bull 2016 Mar;42(2):448-455 [FREE Full text] [doi: 10.1093/schbul/sbv132] [Medline: 26400871]

8. Ben-Zeev D, Kaiser SM, Brenner CJ, Begale M, Duffecy J, Mohr DC. Development and usability testing of FOCUS: a smartphone system for self-management of schizophrenia. Psychiatr Rehabil J 2013 Dec;36(4):289-296 [FREE Full text] [doi: 10.1037/prj0000019] [Medline: 24015913]
9. Bucci S, Barrowclough C, Ainsworth J, Machin M, Morris R, Berry K, et al. Actissist: proof-of-concept trial of a theory-driven digital intervention for psychosis. Schizophr Bull 2018 Aug 20;44(5):1070-1080 [FREE Full text] [doi: 10.1093/schbul/sby032] [Medline: 29566206]
10. Eisner E, Drake RJ, Berry N, Barrowclough C, Emsley R, Machin M, et al. Development and long-term acceptability of ExPRESS, a mobile phone app to monitor basic symptoms and early signs of psychosis relapse. JMIR Mhealth Uhealth 2019 Mar 29;7(3):e11568 [FREE Full text] [doi: 10.2196/11568] [Medline: 30924789]
11. Moritz S, Schröder J, Klein JP, Lincoln TM, Andreou C, Fischer A, et al. Effects of online intervention for depression on mood and positive symptoms in schizophrenia. Schizophr Res 2016 Aug;175(1-3):216-222. [doi: 10.1016/j.schres.2016.04.033] [Medline: 27210726]
12. Ben-Zeev D, Brian RM, Jonathan G, Razzano L, Pashka N, Carpenter-Song E, et al. Mobile health (mhealth) versus clinic-based group intervention for people with serious mental illness: a randomized controlled trial. Psychiatr Serv 2018 Sep 1;69(9):978-985. [doi: 10.1176/appi.ps.201800063] [Medline: 29793397]
13. Berry N, Lobban F, Emsley R, Bucci S. Acceptability of interventions delivered online and through mobile phones for people who experience severe mental health problems: a systematic review. J Med Internet Res 2016 May 31;18(5):e121 [FREE Full text] [doi: 10.2196/jmir.5250] [Medline: 27245693]
14. Schlosser DA, Campellone TR, Truong B, Etter K, Vergani S, Komaiko K, et al. Efficacy of PRIME, a mobile app intervention designed to improve motivation in young people with schizophrenia. Schizophr Bull 2018 Aug 20;44(5):1010-1020 [FREE Full text] [doi: 10.1093/schbul/sby078] [Medline: 29939367]
15. Naslund JA, Aschbrenner KA, Barre LK, Bartels SJ. Feasibility of popular m-health technologies for activity tracking among individuals with serious mental illness. Telemed J E Health 2015 Mar;21(3):213-216 [FREE Full text] [doi: 10.1089/tmj.2014.0105] [Medline: 25536190]
16. Arnold C, Villagonzalo K, Meyer D, Farhall J, Foley F, Kyrios M, et al. Predicting engagement with an online psychosocial intervention for psychosis: exploring individual- and intervention-level predictors. Internet Interv 2019 Dec;18:100266 [FREE Full text] [doi: 10.1016/j.invent.2019.100266] [Medline: 31890619]
17. Torous J, Staples P, Slaters L, Adams J, Sandoval L, Onnela JP, et al. Characterizing smartphone engagement for schizophrenia: results of a naturalist mobile health study. Clin Schizophr Relat Psychoses 2017 Aug 4 epub ahead of print. [doi: 10.3371/CSRP.JTPS.071317] [Medline: 28777029]
18. Hatch A, Hoffman JE, Ross R, Docherty JP. Expert consensus survey on digital health tools for patients with serious mental illness: optimizing for user characteristics and user support. JMIR Ment Health 2018 Jun 12;5(2):e46 [FREE Full text] [doi: 10.2196/mental.9777] [Medline: 29895514]
19. Baup H, Verdoux H. Frequency and pattern of internet use in patients with schizophrenia or bipolar disorders seeking medical information. Psychiatry Res 2017 Jan;247:152-154. [doi: 10.1016/j.psychres.2016.11.028] [Medline: 27893996]
20. Michie S, Yardley L, West R, Patrick K, Greaves F. Developing and evaluating digital interventions to promote behavior change in health and health care: recommendations resulting from an international workshop. J Med Internet Res 2017 Jun 29;19(6):e232 [FREE Full text] [doi: 10.2196/jmir.7126] [Medline: 28663162]
21. Donkin L, Glozier N. Motivators and motivations to persist with online psychological interventions: a qualitative study of treatment completers. J Med Internet Res 2012 Jun 22;14(3):e91 [FREE Full text] [doi: 10.2196/jmir.2100] [Medline: 22743581]
22. Poole R, Simpson SA, Smith DJ. Internet-based psychoeducation for bipolar disorder: a qualitative analysis of feasibility, acceptability and impact. BMC Psychiatry 2012 Sep 13;12(1):139 [FREE Full text] [doi: 10.1186/1471-244X-12-139] [Medline: 22971042]
23. Johansson O, Michel T, Andersson G, Paxling B. Experiences of non-adherence to internet-delivered cognitive behavior therapy: a qualitative study. Internet Interv 2015 May;2(2):137-142. [doi: 10.1016/j.invent.2015.02.006]
24. Nicholas J, Proudfoot J, Parker G, Gillis I, Burckhardt R, Manicavasagar V, et al. The ins and outs of an online bipolar education program: a study of program attrition. J Med Internet Res 2010 Dec 19;12(5):e57 [FREE Full text] [doi: 10.2196/jmir.1450] [Medline: 21169169]
25. Simblett S, Matcham F, Siddi S, Bulgari V, di San Pietro CB, López JH, RADAR-CNS Consortium. Barriers to and facilitators of engagement with mhealth technology for remote measurement and management of depression: qualitative analysis. JMIR Mhealth Uhealth 2019 Jan 30;7(1):e11325 [FREE Full text] [doi: 10.2196/11325] [Medline: 30698535]
26. Gerhards SA, Abma TA, Arntz A, de Graaf LE, Evers SM, Huibers MJ, et al. Improving adherence and effectiveness of computerised cognitive behavioural therapy without support for depression: a qualitative study on patient experiences. J Affect Disord 2011 Mar;129(1-3):117-125. [doi: 10.1016/j.jad.2010.09.012] [Medline: 20889214]
27. Wilhelmsen M, Lillevoll K, Risør MB, Høifødt R, Johansen M, Waterloo K, et al. Motivation to persist with internet-based cognitive behavioural treatment using blended care: a qualitative study. BMC Psychiatry 2013 Nov 7;13(1):296 [FREE Full text] [doi: 10.1186/1471-244X-13-296] [Medline: 24199672]

28. Palmier-Claus JE, Rogers A, Ainsworth J, Machin M, Barrowclough C, Laverty L, et al. Integrating mobile-phone based assessment for psychosis into people's everyday lives and clinical care: a qualitative study. BMC Psychiatry 2013 Jan 23;13:34 [FREE Full text] [doi: 10.1186/1471-244X-13-34] [Medline: 23343329]
29. Jonathan G, Carpenter-Song EA, Brian RM, Ben-Zeev D. Life with FOCUS: a qualitative evaluation of the impact of a smartphone intervention on people with serious mental illness. Psychiatr Rehabil J 2019 Jun;42(2):182-189. [doi: 10.1037/prj0000337] [Medline: 30589278]
30. Forchuk C, Reiss JP, O'Regan T, Ethridge P, Donelle L, Rudnick A. Client perceptions of the mental health engagement network: a qualitative analysis of an electronic personal health record. BMC Psychiatry 2015 Oct 14;15:250 [FREE Full text] [doi: 10.1186/s12888-015-0614-7] [Medline: 26467210]
31. Thomas N, Farhall J, Foley F, Leitan ND, Villagonzalo K, Ladd E, et al. Promoting personal recovery in people with persisting psychotic disorders: development and pilot study of a novel digital intervention. Front Psychiatry 2016;7:196 [FREE Full text] [doi: 10.3389/fpsyt.2016.00196] [Medline: 28066271]
32. Thomas N, Farhall J, Foley F, Rossell SL, Castle D, Ladd E, et al. Randomised controlled trial of a digitally assisted low intensity intervention to promote personal recovery in persisting psychosis: SMART-therapy study protocol. BMC Psychiatry 2016 Sep 7;16(1):312 [FREE Full text] [doi: 10.1186/s12888-016-1024-1] [Medline: 27604363]
33. Anthony WA. Recovery from mental illness: the guiding vision of the mental health service system in the 1990s. Psychiatr Rehabil J 1993;16(4):11-23. [doi: 10.1037/h0095655]
34. Rotondi AJ, Sinkule J, Haas GL, Spring MB, Litschge CM, Newhill CE, et al. Designing websites for persons with cognitive deficits: design and usability of a psychoeducational intervention for persons with severe mental illness. Psychol Serv 2007 Aug;4(3):202-224 [FREE Full text] [doi: 10.1037/1541-1559.4.3.202] [Medline: 26321884]
35. Drake RE, Whitley R. Recovery and severe mental illness: description and analysis. Can J Psychiatry 2014 May;59(5):236-242 [FREE Full text] [doi: 10.1177/070674371405900502] [Medline: 25007276]
36. Braun V, Clarke V. Using thematic analysis in psychology. Qual Res Psychol 2006 Jan;3(2):77-101. [doi: 10.1191/1478088706qp063oa]
37. Barriball KL, While A. Collecting data using a semi-structured interview: a discussion paper. J Adv Nurs 1994 Feb;19(2):328-335. [doi: 10.1111/j.1365-2648.1994.tb01088.x] [Medline: 8188965]
38. Reid K, Flowers P, Larkin M. Exploring lived experience. Psychologist 2005;18(1):20-23 [FREE Full text]
39. Madill A. Realism. In: Given LM, editor. The Sage Encyclopedia of Qualitative Research Methods. Thousand Oaks, CA: Sage Publications; 2008.
40. First M, Spitzer R, Gibbon M, Williams J. User's Guide for the Structured Clinical Interview for Dsm-IV Axis I Disorders: Scid-1 Clinician Version. New York, USA: Biometrics Research Department; 2002.
41. Levitt HM, Bamberg M, Creswell JW, Frost DM, Josselson R, Suárez-Orozco C. Journal article reporting standards for qualitative primary, qualitative meta-analytic, and mixed methods research in psychology: the APA publications and communications board task force report. Am Psychol 2018 Jan;73(1):26-46. [doi: 10.1037/amp0000151] [Medline: 29345485]
42. Bendelin N, Hesser H, Dahl J, Carlbring P, Nelson KZ, Andersson G. Experiences of guided internet-based cognitive-behavioural treatment for depression: a qualitative study. BMC Psychiatry 2011 Jun 30;11(1):107 [FREE Full text] [doi: 10.1186/1471-244X-11-107] [Medline: 21718523]
43. Mohr DC, Cuijpers P, Lehman K. Supportive accountability: a model for providing human support to enhance adherence to ehealth interventions. J Med Internet Res 2011 Mar 10;13(1):e30 [FREE Full text] [doi: 10.2196/jmir.1602] [Medline: 21393123]
44. Nicholas J, Fogarty AS, Boydell K, Christensen H. The reviews are in: a qualitative content analysis of consumer perspectives on apps for bipolar disorder. J Med Internet Res 2017 Apr 7;19(4):e105 [FREE Full text] [doi: 10.2196/jmir.7273] [Medline: 28389420]
45. Titov N, Dear BF, Johnston L, Lorian C, Zou J, Wootton B, et al. Improving adherence and clinical outcomes in self-guided internet treatment for anxiety and depression: randomised controlled trial. PLoS One 2013;8(7):e62873 [FREE Full text] [doi: 10.1371/journal.pone.0062873] [Medline: 23843932]
46. Ryan RM, Deci EL. Intrinsic and extrinsic motivations: classic definitions and new directions. Contemp Educ Psychol 2000 Jan;25(1):54-67. [doi: 10.1006/ceps.1999.1020] [Medline: 10620381]
47. Pung A, Fletcher SL, Gunn JM. Mobile app use by primary care patients to manage their depressive symptoms: qualitative study. J Med Internet Res 2018 Sep 27;20(9):e10035 [FREE Full text] [doi: 10.2196/10035] [Medline: 30262449]
48. Morrison LG, Yardley L, Powell J, Michie S. What design features are used in effective e-health interventions? A review using techniques from critical interpretive synthesis. Telemed J E Health 2012 Mar;18(2):137-144. [doi: 10.1089/tmj.2011.0062] [Medline: 22381060]
49. Yardley L, Spring BJ, Riper H, Morrison LG, Crane DH, Curtis K, et al. Understanding and promoting effective engagement with digital behavior change interventions. Am J Prev Med 2016 Nov;51(5):833-842. [doi: 10.1016/j.amepre.2016.06.015] [Medline: 27745683]
50. Yardley L, Morrison L, Bradbury K, Muller I. The person-based approach to intervention development: application to digital health-related behavior change interventions. J Med Internet Res 2015 Jan 30;17(1):e30 [FREE Full text] [doi: 10.2196/jmir.4055] [Medline: 25639757]

51. Seed T, Fox JR, Berry K. The experience of involuntary detention in acute psychiatric care. A review and synthesis of qualitative studies. Int J Nurs Stud 2016 Sep;61:82-94. [doi: 10.1016/j.ijnurstu.2016.05.014] [Medline: 27314181]
52. Mohr DC, Schueller SM, Montague E, Burns MN, Rashidi P. The behavioral intervention technology model: an integrated conceptual and technological framework for ehealth and mhealth interventions. J Med Internet Res 2014 Jun 5;16(6):e146 [FREE Full text] [doi: 10.2196/jmir.3077] [Medline: 24905070]
53. Aref-Adib G, O'Hanlon P, Fullarton K, Morant N, Sommerlad A, Johnson S, et al. A qualitative study of online mental health information seeking behaviour by those with psychosis. BMC Psychiatry 2016 Jul 11;16:232 [FREE Full text] [doi: 10.1186/s12888-016-0952-0] [Medline: 27400874]
54. Walsh A, Richards D. Experiences and engagement with the design features and strategies of an internet-delivered treatment programme for generalised anxiety disorder: a service-based evaluation. Brit J Guid Couns 2016 Feb 28;45(1):16-31. [doi: 10.1080/03069885.2016.1153039]
55. Agar-Jacomb K, Read J. Mental health crisis services: what do service users need when in crisis? J Ment Health 2009 Jul 6;18(2):99-110. [doi: 10.1080/09638230701879227]
56. Rotondi AJ, Eack SM, Hanusa BH, Spring MB, Haas GL. Critical design elements of e-health applications for users with severe mental illness: singular focus, simple architecture, prominent contents, explicit navigation, and inclusive hyperlinks. Schizophr Bull 2015 Mar;41(2):440-448 [FREE Full text] [doi: 10.1093/schbul/sbt194] [Medline: 24375458]
57. Mohr DC, Weingardt KR, Reddy M, Schueller SM. Three problems with current digital mental health research . . . and three things we can do about them. Psychiatr Serv 2017 May 1;68(5):427-429 [FREE Full text] [doi: 10.1176/appi.ps.201600541] [Medline: 28412890]
58. Depp C, Perivoliotis D, Holden J, Dorr J, Granholm E. Single-session mobile-augmented intervention in serious mental illness: a three-arm randomized controlled trial. Schizophr Bull 2019 Jun 18;45(4):752-762. [doi: 10.1093/schbul/sby135] [Medline: 30281086]
59. McGlashan TH, Levy ST, Carpenter WT. Integration and sealing over. Clinically distinct recovery styles from schizophrenia. Arch Gen Psychiatry 1975 Oct;32(10):1269-1272. [doi: 10.1001/archpsyc.1975.01760280067006] [Medline: 1180660]
60. McGlashan TH, Docherty JP, Siris S. Integrative and sealing-over recoveries from schizophrenia: distinguishing case studies. Psychiatry 1976 Nov;39(4):325-338. [doi: 10.1080/00332747.1976.11023903] [Medline: 996183]
61. Heath J, Williamson H, Williams L, Harcourt D. 'It's just more personal': using multiple methods of qualitative data collection to facilitate participation in research focusing on sensitive subjects. Appl Nurs Res 2018 Oct;43:30-35. [doi: 10.1016/j.apnr.2018.06.015] [Medline: 30220360]
62. Johnson DR, Scheitle CP, Ecklund EH. Beyond the in-person interview? How interview quality varies across in-person, telephone, and Skype interviews. Soc Sci Comput Rev 2019 Dec 11:1-17. [doi: 10.1177/0894439319893612]

## Abbreviations

**SMART:** Self-Management and Recovery Technology

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Review

# Surveying the Role of Analytics in Evaluating Digital Mental Health Interventions for Transition-Aged Youth: Scoping Review

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## Abstract

**Background:** Consumer-facing digital health interventions provide a promising avenue to bridge gaps in mental health care delivery. To evaluate these interventions, understanding how the target population uses a solution is critical to the overall validity and reliability of the evaluation. As a result, usage data (analytics) can provide a proxy for evaluating the engagement of a solution. However, there is paucity of guidance on how usage data or analytics should be used to assess and evaluate digital mental health interventions.

**Objective:** This review aimed to examine how usage data are collected and analyzed in evaluations of mental health mobile apps for transition-aged youth (15-29 years).

**Methods:** A scoping review was conducted using the Arksey and O'Malley framework. A systematic search was conducted on 5 journal databases using keywords related to usage and engagement, mental health apps, and evaluation. A total of 1784 papers from 2008 to 2019 were identified and screened to ensure that they included analytics and evaluated a mental health app for transition-aged youth. After full-text screening, 49 papers were included in the analysis.

**Results:** Of the 49 papers included in the analysis, 40 unique digital mental health innovations were evaluated, and about 80% (39/49) of the papers were published over the past 6 years. About 80% involved a randomized controlled trial and evaluated apps with information delivery features. There were heterogeneous findings in the concept that analytics was ascribed to, with the top 3 being engagement, adherence, and acceptability. There was also a significant spread in the number of metrics collected by each study, with 35% (17/49) of the papers collecting only 1 metric and 29% (14/49) collecting 4 or more analytic metrics. The number of modules completed, the session duration, and the number of log ins were the most common usage metrics collected.

**Conclusions:** This review of current literature identified significant variability and heterogeneity in using analytics to evaluate digital mental health interventions for transition-aged youth. The large proportion of publications from the last 6 years suggests that user analytics is increasingly being integrated into the evaluation of these apps. Numerous gaps related to selecting appropriate and relevant metrics and defining successful or high levels of engagement have been identified for future exploration. Although long-term use or adoption is an important precursor to realizing the expected benefits of an app, few studies have examined this issue. Researchers would benefit from clarification and guidance on how to measure and analyze app usage in terms of evaluating digital mental health interventions for transition-aged youth. Given the established role of adoption in the success of health information technologies, understanding how to abstract and analyze user adoption for consumer digital mental health apps is also an emerging priority.

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**KEYWORDS**

user engagement; mobile apps; mHealth; telemedicine; mental health; adolescent; data analytics

# *Introduction*

## Background

Transition-aged youth, youth between the ages of 15 and 29 years, may face difficult challenges during the transition from childhood to adulthood [1]. The ongoing challenges to provide adequate support for transition-aged youth are reflected by the observed increase in child and adolescent mental health problems [2-5]. In fact, over half of all mental health disorders among adults begin during childhood and adolescence [6,7]. And currently, mental health and substance use disorders are responsible for 25% of all years lived with disability [8]. In Canada, 11% of youth aged 15-24 years reported experiencing symptoms of depression, and 14% reported experiencing suicidal thoughts in the past [9]. These issues are further complicated by the ongoing stigma related to mental health issues [10,11] and the lower likelihood among this population to seek help [12-14]. Novel approaches to support the mental health needs and demands of this population are warranted to address these challenges [15].

## Mobile Health Interventions

Mobile health (mHealth) interventions have been identified as a promising avenue to bridge the gap between seeking help and accessing mental health resources for the youth [16-18]. The youth are well acquainted with the use of technology [18], and mobile phone use is deeply embedded in their daily lives [19]. In addition, qualitative interviews with youth show positive perceptions of mHealth interventions for mental health needs [20]. Reviews on digital mHealth interventions for youth in general [21] and college students as a group [22] have suggested that mHealth interventions can be powerful platforms for improving the overall well-being or enhancing mental health treatments among this population. The promising effectiveness of mHealth as a means of delivering mental health interventions among the youth has led to the proliferation of digital technologies.

Despite these advances, the proliferation of and interest in youth-oriented mental health apps do not always directly translate to real-world outcomes. Numerous explanations exist, and a major barrier identified by Torous et al [23] is the low engagement or uptake of these digital interventions. Since engagement is often considered a prelude to the effectiveness of digital interventions, this warrants a closer examination of how end user engagement is being measured across evaluations of youth-targeted mHealth interventions. [24]. As highlighted in a recent review of this area by Pham et al [25], the unique challenges in measuring and evaluating engagement are not limited to the heterogeneous terms used in reporting engagement levels (ie, adherence, usage, feasibility, adoption, and activity) but extend to the depth and breadth of analytics metrics being selected for measurement. This creates difficulty in selecting, interpreting, comparing, and aggregating data on engagement metrics related to these youth-targeted mHealth interventions. To determine the current state of engagement reporting and inform future efforts, we performed a scoping review of analytic metrics that were measured, reported, and used to inform the evaluation of youth-targeted digital mental health interventions. This study was used to inform the development of a randomized controlled trial (RCT) to evaluate Thought Spot [26-29], a mobile app designed to foster mental health and wellness help-seeking in transition-aged youth across the Greater Toronto Area.

# *Methods*

## Overview

We conducted a scoping review using the framework proposed by Arksey and O'Malley [30], which consists of 5 main processes: (1) identifying the research question, (2) identifying relevant papers, (3) selecting studies, (4) extracting the data, and (5) collating and summarizing the data and results.

## Identifying the Research Question

The main objective of this scoping review was to explore how analytics metrics are measured, reported, and used to evaluate mHealth interventions that target mental health–related issues among transition-aged youth. Under this overarching main research objective, we sought to answer the following 2 research questions to guide the review and analysis:

1. Which analytics metrics are used in evaluation studies for mHealth interventions that target transition-aged youth?
2. How do user activity and usage metrics contribute to the interpretation of study data?

## Identifying Relevant Papers

A search strategy was developed in consultation with a specialist librarian and the research team. A search using key terms such as adoption, evaluation, mental health, transition-aged youth, and mHealth was conducted in July 2018, from 5 databases: Cumulative Index of Nursing and Allied Health Literature (CINAHL), EMBASE, Medical Literature Analysis and Retrieval System (MEDLINE), PsycINFO, and Cochrane Central Register of Controlled Trials (CENTRAL). The full-search strategy for one of the databases (MEDLINE) is presented in Multimedia Appendix 1. Given the timeline of mHealth proliferation, it was deemed adequate to include only papers from the past 10 years (2008-2018) in the initial search [31]. All peer-reviewed literature was included in the review. The search was updated in June 2019, and additional papers were included in the analysis.

### Selecting Studies

After removal of duplicate papers, titles and abstracts were screened independently by 2 authors (BL and JS). There were 3 inclusion criteria: the papers examined mental health mHealth interventions designed for transition-aged youth (aged 15-29 years), included an analysis of engagement or user activity metrics, and published in English. For studies that did not indicate a specific age range, the mean and SD of the sample were used to determine the eligibility for inclusion. Studies containing only self-reported usage data or those that were developed for clinician use only were excluded, along with reviews, conference reports, and dissertations. No restrictions were placed on the type of research design or the method of comparison being made to ensure that a broad selection of studies were captured for this review.

Inter-rater reliability in screening by both reviewers was enhanced by first conducting a pilot screen of 100 papers. Pilot screens were completed independently until a satisfactory kappa statistic >0.7 [32] was reached. Two reviewers then conducted title and abstract screening independently for all papers using Abstrackr (Center for Evidence Synthesis in Health, Brown University) [33]. Any discrepancies were resolved through discussion, resulting in a consensus.

### Extracting Data

A data extraction form adapted from the Cochrane data extraction template [34] was used to extract data from each paper. A summary of the data extracted from each paper is given in Multimedia Appendix 2. This process was also performed independently by 2 authors (BL and JS) to ensure that all relevant data were accurately captured. The data were then collated into a spreadsheet for further analysis. Extracted study details included study design (eg, RCT, observational), sample size, participant characteristics, targeted condition, main research question, and primary and secondary outcomes. The target condition was extracted and categorized using the 5th edition of the *Diagnostic and Statistical Manual of Mental Disorders* [35], and interventions were classified using the *Classification of Digital Health Interventions* [36] from the World Health Organization (WHO). Additional data were also gathered based on the research questions outlined above, such as usage metrics, terminology, results, and method of analysis.

### Summarizing the Data

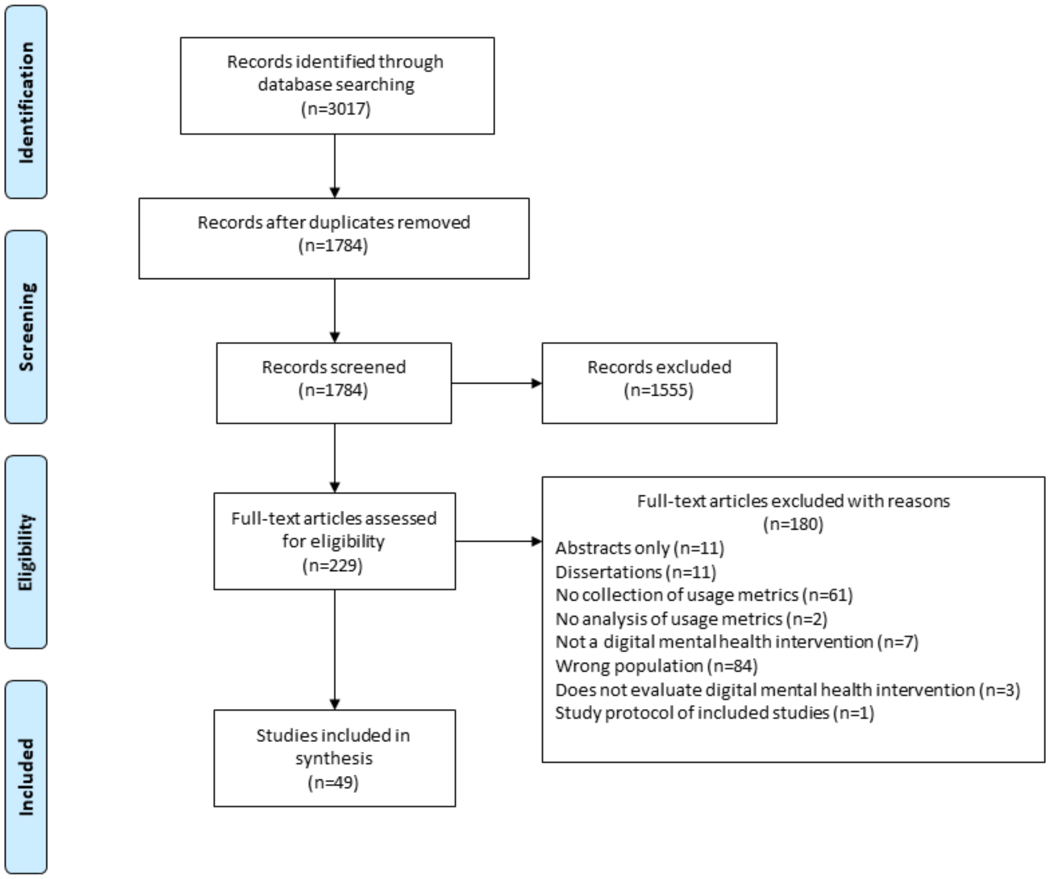
Quantitative and qualitative analyses of data were conducted. Descriptive statistics (eg, means, medians) were collected and used to characterize and describe each included paper. We identified the metrics of our included papers using a similar approach to that of another recently published review [25]. The themes were reviewed and extracted using a content analysis approach [37] to address the second research question. Two members of the research team (BL and JS) reviewed the data and ensured comprehensiveness and accuracy.

## Results

### Selection of Included Studies

An overview of the selection of included studies is presented using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses [38] diagram in Figure 1. The database search identified 1784 nonduplicated papers. The kappa statistic, a measure of inter-rater reliability, for the pilot screen was 0.72, meeting the above-defined threshold. Following the title and the abstract review, 229 papers were fully reviewed and assessed based on the inclusion and exclusion criteria. This full-text screening was conducted independently by 2 authors (BL and JS).

**Figure 1.** Preferred Reporting Items for Systematic Reviews and Meta-Analyses diagram of included studies.



## Characteristics of Included Papers

The characteristics of and references to the included studies are described in Table 1. Of the 49 papers included in this scoping review, there were 40 full reports that collected and reported usage data and 9 protocol papers that indicated an analysis of usage data in the evaluation. The findings identified 40 unique digital mental health interventions that were evaluated. Although the search strategy included studies published between 2008 and 2019, 80% (39/49) of the studies identified for inclusion were published within the last 6 years (2014-2019). The largest number of studies were conducted in the United States (21/49) and Australia (12/49).

A large number of studies have examined the efficacy or effectiveness [39-69] of the intervention in supporting individuals (eg, symptoms) as their primary objective. Studies that included other constructs (eg, feasibility [51,66,70-73], acceptability [51,57,66,69-75]) as primary objectives were typically in the earlier stages of development. In terms of methodology, the majority of studies (38/49) used or intended to use RCT methodology to conduct their evaluation. The remaining 11 studies used quasi-experimental approaches, including observational studies and single-group pretest posttest design. Studies using quasi-experimental approaches seem to be in the earlier stages of development. The sample size (or expected sample size) had a median of 100 participants and ranged from 10 to 8242 participants. Approximately 51% (25/49) of the included studies had up to 100 participants for analysis. The length of exposure to the intervention was also captured, and 47 of the 49 studies reported the duration of intervention. Approximately 74% (36/49) of the studies evaluated participants after using the intervention for 1 to 3 months. About 22% (11/49) of the studies asked users to use the app for more than four months.

Classification using the WHO Classification of Digital Health Interventions [36] revealed that several mental health apps (n=11) exhibited more than one function. Three features that were most commonly found among the evaluated interventions were targeted client communication (n=39), client-to-client communication (n=8), and on-demand information services (n=5). These interventions also targeted a range of mental health–related conditions, with depressive disorders as the most common condition (n=13), followed by interventions targeting participants' overall well-being (n=11). Other targeted conditions included anxiety disorders (n=2), family violence (n=1), feeding and eating disorders (n=6), neurodevelopmental disorders (n=1), schizophrenia spectrum and other psychotic disorders (n=4), substance use and addictive disorders (n=6). The paper on neurodevelopmental disorders is a study conducted by Backman et al [76] that aims to deliver psychoeducation to adolescents with autism spectrum disorde. Five studies developed interventions that targeted comorbid conditions such as cooccurring depression and alcohol use.

**Table 1.** Characteristics of included studies (N=49).

| Characteristic | Number of studies, n (%) | References |
|---|---|---|
| **Type of paper** | | |
| Full | 40 (82) | [39,40,42-46,49-52,54-58,61-63,65-71,73,74,76-87] |
| Protocol | 9 (18) | [41,47,48,53,59,60,64,72,75] |
| **Year of publication** | | |
| 2008 | 1 (2) | [39] |
| 2009 | 1 (2) | [40] |
| 2010 | 2 (4) | [41,42] |
| 2011 | 1 (2) | [43] |
| 2012 | 2 (4) | [44,45] |
| 2013 | 3 (6) | [46,70,77] |
| 2014 | 8 (16) | [47-50,78-81] |
| 2015 | 5 (10) | [51-54,87] |
| 2016 | 4 (8) | [55,71-73] |
| 2017 | 6 (12) | [56-59,82,83] |
| 2018 | 12 (25) | [60-63,66-69,74,76,84,86] |
| 2019 | 4 (8) | [64,65,75,85] |
| **Country of study** | | |
| Australia | 12 (25) | [41,42,47,53,56,58,65,67,70,71,73,74] |
| Canada | 1 (2) | [54] |
| Germany | 2 (4) | [44,62] |
| Ireland | 2 (4) | [48,66] |
| Japan | 1 (2) | [85] |
| The Netherlands | 3 (6) | [64,75,83] |
| New Zealand | 1 (2) | [87] |
| Norway | 1 (2) | [80] |
| Romania | 1 (2) | [59] |
| Spain | 1 (2) | [60] |
| Sweden | 1 (2) | [76] |
| United Kingdom | 2 (4) | [39,77] |
| United States | 21 (43) | [40,43,45,46,49-52,55,57,61,63,68,69,72,78,79,81,82,84,86] |
| **Study sample size** | | |
| ≤100 | 25 (51) | [40,46,48,50,51,54,55,57-59,61,63,64,68,70-72,75,76,78,79,81-83,85] |
| 101-1000 | 17 (35) | [39,42,44,45,47,49,52,56,62,65-67,69,73,84,86,87] |
| >1000 | 6 (12) | [43,53,60,74,77,80] |
| Unknown | 1 (2) | [41] |
| **Duration of intervention** | | |
| ≤1 month | 10 (20) | [42,47,52,56,61,69,70,73,79,81] |
| 2-3 months | 26 (53) | [39-41,45,48-51,53,54,57-59,62,63,66,67,71,72,75,78,80,83,85-87] |
| 4-12 months | 8 (16) | [44,46,60,64,65,68,76,77] |
| >12 months | 3 (6) | [55,74,82] |
| Unknown | 2 (4) | [43,84] |
| **Type of app**[a] | | |

| Characteristic | Number of studies, n (%) | References |
|---|---|---|
| On-demand information services | 5 (10) | [56,74,77,85,87] |
| Client-to-client communication | 8 (16) | [44,48,49,52,70-72,83] |
| Personal health tracking | 4 (8) | [48,61,65,66] |
| Targeted client communication | 39 (80) | [39-42,44-48,50-55,57-61,63-73,76,78-84] |
| Untargeted client communication (eg, modular delivery) | 4 (8) | [43,62,75,86] |
| **Study design** | | |
| Randomized controlled trials | 38 (78) | [39-41,43-56,58-60,62-65,67-69,72,73,77-84,86] |
| Quasi-experimental designs | 11 (22) | [42,57,61,66,70,71,74-76,85,87] |
| **Mental health condition** | | |
| Anxiety disorders | 2 (4) | [41,48] |
| Depressive disorders | 13 (27) | [40,46,52-55,58,61,71,78,80,82,85] |
| Feeding and eating disorders | 6 (12) | [44,45,49,51,59,67] |
| Other (family violence) | 1 (2) | [83] |
| Overall well-being | 11 (22) | [42,56,57,62,69,74,75,77,79,86,87] |
| Schizophrenia spectrum and other psychotic disorders | 4 (8) | [50,63,70,72] |
| Neurodevelopmental disorders | 1 (2) | [76] |
| Substance use and addictive disorders | 6 (12) | [39,43,60,68,81,84] |
| Mixed | 5 (10) | [47,64-66,73] |

[a] On the basis of World Health Organization Classification of Digital Health Interventions [36]. Some apps report exhibiting multiple functions.

## Analytics Metrics and Analysis

All studies examined usage data in some aspects of their evaluation, and most papers were ascribed to one or more of the following constructs: user adherence [40,46,49-51,53,55,62,64,75,80,82,85], engagement [47,48,52,56,61,65,67,77,79,84], or acceptability [45,57,71]. Although adoption was included in our search, none of the reviewed studies used analytics as a proxy to measure that indicator.

A summary of the findings for analytics metrics and analysis is provided in Table 2. Fifty percent (25/49) of the studies collected 1 or 2 metrics to examine user activity, and 29% (14/49) collected more than four metrics. Most studies had a limited amount of user activity data that were used to explore and understand how participants used their digital interventions.

Across the reviewed studies, different types of metrics were used to evaluate the level of user activity in these interventions. Overall, a heterogeneous selection of metrics was collected, with the number of modules completed (n=27/49) and the session duration (n=24) being the most common metrics. In particular, a few studies collected metrics on the number of times different features were used (n=18). Because these features were highly specific to the intervention being evaluated (ie, number of likes, number of journal entries), these unique metrics were collapsed into a general category called *number of features used*. The *other* category consisted of metrics that did not fall into the common categories and included the bounce rate, the referral source, and the number of characters. The bounce rate and the referral source were collected by 1 of the studies [83] that used Google Analytics [88].

In terms of how metrics were analyzed, many studies [40,42,44-48,50,54,57-59,62,63,65,66,68-70,72-77,79,80,82,85,86] presented usage metrics separately from the main study data using descriptive methods, which included the overall counts, frequencies, means, or SDs. Several studies [39,84] had the main objective of examining how different interventions (eg, behavioral activation) impacted user engagement on the app. These studies conducted analyses using hypothesis testing techniques (eg, chi-square test, *t* tests). Many studies [43,53,60,61,78,81] also attempted to examine if different levels of user activity had a differential effect on the main study outcomes. For example, Paschall et al [43] analyzed reductions in alcohol use by stratifying the course completion rate into 3 categories: high users (70%), medium users (30%-69%), and low users (0%-29%), and reported differential effects within each group. Other studies employed regression analysis and identified varying results. For example, Bidargaddi et al [56] evaluated an app on resource finding and found that the number of log-ins was not associated with the ecological momentary assessment outcomes.

**Table 2.** Types of usage metrics collected in included studies (N=49).

| Characteristic | Number of studies, n (%) | References |
|---|---|---|
| **Number of usage metrics analyzed** | | |
| 1 | 17 (35) | [39,41,43,50,56,58-60,67,73,76,77,81,84-87] |
| 2 | 8 (16) | [42,45,47,51,54,68,69,80] |
| 3 | 10 (20) | [40,44,49,53,62,64,65,72,75,82] |
| 4+ | 14 (29) | [46,48,52,55,57,61,63,66,70,71,74,78,79,83] |
| **Type of metrics collected (multiselect)** | | |
| Number of clicks | 1(2) | [61] |
| Number of features used | 18 (37) | [40,41,46,48,51,52,57,62,63,65,66,68,69,71,72,74,79,83] |
| Number of log-ins | 20 (41) | [49,52,54-57,61-64,66,70-72,74,75,79,80,83,87] |
| Number of modules | 27 (55) | [43,45-47,50,53-55,57,58,60,62,64,66,67,69,70,73-76,78-82,86] |
| Number of page views | 10 (20) | [44,48,49,51,61,70,74,77,79,83] |
| Number of posts | 5 (10) | [44,63,70,71,78] |
| Number of sessions | 9 (18) | [39,42,46,48,52,53,55,74,78] |
| Rate of return | 4 (8) | [70,71,74,83] |
| Session duration | 24(49) | [40,42,45,46,48,49,52,53,55,57,61,64-66,68,70,74,75,78,79,82-85] |
| Other (eg, calculated metrics) | 14 (29) | [40,44,46,47,52,55,59,61,65,70,72,74,82] |

Although some studies have also reported similar results [49,51,84], associations between specific analytic measures and outcomes have been identified. For example, Saekow et al [51] noted correlations between the number of log-ins and physical outcome measures of the Eating Disorder Examination Questionnaire. Logsdon et al [61] also found that the duration of a depression intervention was associated with reported attitudes of the participants. Another study on CATCH-IT [78], a module-based intervention for depression, also found that an increased duration on the website was associated with changes in depressive symptoms.

Two studies incorporated more sophisticated metrics. Stallman and Kavanagh [74] leveraged the Google Analytics engine to examine if referral source as a metric influenced their outcomes. They found that different referral sources resulted in different expectations and disparities in user activities. In addition, Schlosser et al [63] separated their user activity data into active use and passive use by calculating the active use rate. The authors [63] defined active engagement as interacting with the features of the app and passive use as logging onto the app but not interacting with a specific feature of the app (ie, posting a moment, completing a challenge, participating in peer interactions). However, their exploration did not find any significant relationships between these user activity metrics and changes in primary and secondary outcomes.

The findings of this scoping review will also be used to inform the selection of analytics metrics to be examined as a potential exploratory component of a larger RCT evaluating an mHealth intervention, Thought Spot [26].

## Discussion

### Principal Findings

This scoping review explores how usage data are characterized and analyzed in evaluations of digital mental health innovations for transition-aged youth. There is an unprecedented demand to address current concerns and gaps in adolescent mental health [89,90], and the increasing ubiquity of mobile apps provides a unique opportunity to do so [91]. The recent nature of the 49 papers included in this review suggests a growing movement toward integrating analytics into mHealth evaluations [25]. In fact, the observed diversity in objectives, sample size, and duration of exposure suggests that analytics can bring value in evaluations of efficacy, effectiveness, and feasibility studies. Analytics is also of particular interest in the mental health domain because of its potential role in digital phenotyping, which is a growing area of study that explores the intersection of behavior and passively collected data [92-94]. As a result, understanding the value and significance of analytics can help to enhance our understanding and applications in digital psychiatry [95]. However, despite the increasing ubiquity of analytics in evaluations, the overall findings of the current review highlight several gaps in evidence [84].

Foremost, there was significant heterogeneity in the construct that analytics was ascribed to. For example, Bidargaddi et al [56] used the term *engagement*, whereas Rickhi et al [54] used the term *program use*, even though both studies used the number of log-ins as their usage metric. Similar variability was also found in a recent review of analytic indicators by Pham et al [25] who suggest that distinctions between certain constructs such as acceptance and engagement are emerging. Likewise, although *engagement* was found to be the most common construct used to describe analytics, it is not surprising because there is a significant body of literature on conceptualizing this term [25,96,97]. As such, the emerging demarcation of these terminologies will likely foster guidance on the role of analytics in measuring these constructs.

In addition, although adoption was included in the search strategy, no studies in our included papers examined adoption specifically and/or used analytics as a proxy to abstract the construct. This is interesting in contrast to literature in clinical informatics where adoption is often an end goal for implementation of technology [98-100] and is well described in implementation frameworks [101]. For example, the clinical adoption metamodel [101] uses the definition from Hall [102] and describes adoption as the process (eg, activities and decisions) of integrating a specific technology into an organization. Similarly, Roger's diffusion of innovation theory defines adoption as "the decision to make full use of an innovation as the best course of action" [103]. Although *adoption* was a keyword included in our search strategy, we are unable to identify any studies that used analytics to measure adoption. The disparity between the clinical informatics literature and that of consumer informatics literature is intriguing. Increasing awareness of the potential of digital mental health in connecting care and empowering patients to participate in their own care [104] requires users to utilize the technology as appropriate to successfully realize the intended benefits [23]. Addressing this discordance is particularly important, given that Torous et al [105] noted that interest in technology does not necessarily result in the uptake and usage of technology. As such, similar to clinical informatics, it may be valuable to understand and characterize the successful adoption of consumer health information technology [63].

Furthermore, understanding the process of how transition-aged youth decide to adopt technology would provide further insight into the characteristics of successful adoption [23,39,84]. Transition-aged youth are part of the generation where access to the internet and usage of mobile apps are fundamental to their daily lives [106]. As commented by Bewick et al [39], it is unclear how consumers choose to engage and uptake technologies. Although approaches such as user-centered design methodology [107] and gamification [108] have made significant progress in closing the gap between perceived and actual user needs, real-world engagement remains fairly low and heterogeneous [109]. As such, identifying predictors of uptake by understanding how this population adopts these types of technology may help inform the development of an app that will result in adoption by the intended population [49,55,74,80,84].

The other key finding of this review is the significant heterogeneity in the number and types of metrics collected. We observed that most studies collected 1 or 2 metrics and usually included the number of modules completed and the session duration. These findings are in contrast to a similar review by Pham et al [25] on chronic diseases, which found that the number of recorded measures and the frequency of interactions were the most prevalent metrics collected. Given that many studies evaluated computerized cognitive-behavioral therapy programs that are modular in nature, it is not surprising that module completion was most commonly found in this review. Nevertheless, the significance and value of each of these metrics are unclear. At the time of writing this paper, a review by Pham et al [25] attempted to address this issue by categorizing metrics into different components of engagement: amount, breadth, depth, and duration. In addition, Pham et al [25] attempted to provide guidance on how to select appropriate metrics for an evaluation. Although they have made significant progress on some of these issues [25], we believe that the importance and consistency of this issue warrants more in-depth discussion.

The heterogeneity in analytics metrics between studies also generates another level of complexity for analysis. For the various metrics selected, many studies often characterized their analytics findings as constituting high usage [45,50,58,63,72,73,79] or low usage [39,73,80]. However, there does not seem to be a standard as to what constitutes these demarcations [81]. Although it is likely that the boundaries of high or low usage are relative to authors' expectations, the lack of a standardized definition to demarcate high or low usage can generate confusion. We found that many studies referenced other studies to define high or successful usage levels [50,70,71,81]. However, it is unclear if the threshold used for defining high usage in a single evaluation merits sufficient external validity to be used by others. Several studies also referred to the construct of *dosage* [54,80,81], particularly with respect to if users have received sufficient dosage to reap the benefits of the app. Although usage data may help provide insight into amount of usage, it is unclear how to determine if usage becomes sufficient, insufficient, or too much [61,80-82]. Identifying robust methods to evaluate the complexity of analytic data and understanding how these levels are demarcated to contribute to the validity of the evaluation would be useful.

Similar to the observations made by Pham et al [25], many analyses of analytics in our included studies were limited to descriptive analysis, with only a few studies examining the relationship between analytic metrics and primary outcomes. Although these results were primarily mixed, it is also unclear what significance these correlations had in the overall evaluation. Studies that identified a correlation [78,81] suggested that this finding indicated that usage of the app was beneficial for the specific outcome. In other studies where no relationship was identified between analytics and outcomes, some authors questioned if this finding reflected a lack of efficacy of the mHealth app [56]. A few studies also conducted a per-protocol analysis in addition to the traditional intention-to-treat approach [110]. Although intention-to-treat [110] is the gold standard for RCTs, the high attrition of electronic health (eHealth) solutions may be too conservative in evaluating the actual impact on users who have sustained use of a solution [43].

## Limitations

Several limitations should be noted when interpreting the findings of this scoping review. Because consumer health informatics has become popularized only over the last decade [31], we focused our review on the literature from 2008 onward. Although our findings suggest that most papers have been published within the last 6 years, it is possible that we might have missed papers outside of this window in our search strategy. In addition, due to our scope of work on Thought Spot

[26,27,29], our search was limited to examining interventions designed exclusively for transition-aged youth. Because we excluded papers evaluating interventions for other populations (eg, adults) and disease sites (eg, cardiology), there may have been evidence and guidance on the use of analytics in other areas of health care [25]. Evaluating how analytics is applied in other domains of health care may provide more comprehensive insight into the role of analytics in consumer health informatics. It is also interesting to note that most of the papers included in this review were published in North America and Europe, and there was a lack of studies from other countries, including those in Asia and Africa. An evaluation of how adoption and engagement are measured in studies conducted in other countries is warranted.

A second limitation is that, as per guidelines established for scoping reviews [30], we did not evaluate the quality of the included studies. In addition, our review focused on scientific literature and did not include interviews with key stakeholders or a survey of the gray literature. Future research should explore these other sources of literature and evaluate the quality of the studies identified for subsequent systematic reviews.

Finally, it should be noted that, due to the limited number of papers in this scoping review, we did not limit our analyses by mental health conditions and types of research designs. In particular, it would be useful to examine how analytics is used to support the evaluation of different solutions and objectives. Studies such as Torous et al [111] and Connolly et al [112] have identified that individuals with different mental health conditions and culture can impact their engagement with technology. Future work should evaluate how these differences should be explored in the evaluation of adoption and engagement with technology.

### Future Directions

This scoping review provides a preliminary insight into the role of analytics in evaluating mHealth apps for transition-aged youth and identifies both progress that has been made and future areas of exploration. Most importantly, this review adds to the sparse literature on analytics and highlights the need for researchers to assess and standardize how to integrate analytics into their evaluation plans [25]. The addition of more case studies on analytics may help to identify emergent patterns that help us understand how transition-aged youth decide to adopt a solution to address their needs [14].

In addition, several areas of exploration have been identified for researchers. As suggested by Pham et al [25], there is currently no guidance on how to maximize the value of these data. However, in other fields such as marketing, analytics is a robust component in evaluating the success of products and solutions [113]. Thus, it is important to understand how to analyze these findings. This may include knowing how to identify thresholds for high and low users as well as recognizing the significance of correlations and relationships between analytic metrics and primary outcomes. Given that these thresholds may differ between different clinical conditions and methodologies, subanalyses examining how adoption and engagement are explored for different populations (eg, cultures) and research designs may be of interest. Additionally, similar to the progress made in clinical informatics [98-100], understanding the characteristics and predictors of successful adoption of a consumer technology would provide insights into developing a roadmap toward successful mHealth development for transition-aged youth [114].

### Conclusions

This scoping review provided initial insights into the role of analytics in evaluating mobile mental health apps (mHealth) for transition-aged youth. Our analysis of 49 studies published between 2008 and 2019 revealed that the use of analytics is becoming increasingly ubiquitous in evaluating mHealth apps for transition-aged youth. Despite recent progress in the use of analytics, there is still heterogeneity in understanding the significance and value of analytics in these evaluations. In addition, the lack of guidance on metrics selection and analysis warrants future exploration. As digital mental health care continues to grow in popularity, particularly for transition-aged youth, understanding analytics and its impact on evaluations would help to streamline the journey toward using digital interventions to foster better mental health care for this population.

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## Authors' Contributions

DW, JS, A Johnson, AA-Jaoude, and EH conceived the idea for this project. BL and JS developed the search strategy and conducted a screening process. BL and JS conducted data extraction and analysis with support from DW, AJ, AA-Jaoude, and EH. BL and JS led to the writing of the manuscript. EH and DW made substantial edits to the manuscript before submission. All authors have reviewed and approved this manuscript.

## Conflicts of Interest

None declared.

Multimedia Appendix 1
Sample search strategy for scoping review.
[DOCX File , 16 KB - mental_v7i6e15942_app1.docx ]

Multimedia Appendix 2
Data extraction table for scoping review.
[XLSX File (Microsoft Excel File), 34 KB - mental_v7i6e15942_app2.xlsx ]

## References

1. Mandarino K. Transitional-age youths: barriers to accessing adult mental health services and the changing definition of adolescence. J Hum Behav Soc Environ 2014 Apr 30;24(4):462-474. [doi: 10.1080/10911359.2013.835760]
2. Sawyer SM, Afifi RA, Bearinger LH, Blakemore S, Dick B, Ezeh AC, et al. Adolescence: a foundation for future health. Lancet 2012 Apr 28;379(9826):1630-1640. [doi: 10.1016/S0140-6736(12)60072-5] [Medline: 22538178]
3. Bor W, Dean AJ, Najman J, Hayatbakhsh R. Are child and adolescent mental health problems increasing in the 21st century? A systematic review. Aust N Z J Psychiatry 2014 Jul;48(7):606-616. [doi: 10.1177/0004867414533834] [Medline: 24829198]
4. Lipson SK, Lattie EG, Eisenberg D. Increased rates of mental health service utilization by US college students: 10-year population-level trends (2007-2017). Psychiatr Serv 2019 Jan 1;70(1):60-63 [FREE Full text] [doi: 10.1176/appi.ps.201800332] [Medline: 30394183]
5. Burstein B, Agostino H, Greenfield B. Suicidal attempts and ideation among children and adolescents in US emergency departments, 2007-2015. JAMA Pediatr 2019 Jun 1;173(6):598-600. [doi: 10.1001/jamapediatrics.2019.0464] [Medline: 30958529]
6. Kessler RC, Wang PS. The descriptive epidemiology of commonly occurring mental disorders in the United States. Annu Rev Public Health 2008;29:115-129. [doi: 10.1146/annurev.publhealth.29.020907.090847] [Medline: 18348707]
7. Paus T, Keshavan M, Giedd JN. Why do many psychiatric disorders emerge during adolescence? Nat Rev Neurosci 2008 Dec;9(12):947-957 [FREE Full text] [doi: 10.1038/nrn2513] [Medline: 19002191]
8. Erskine HE, Moffitt TE, Copeland WE, Costello EJ, Ferrari AJ, Patton G, et al. A heavy burden on young minds: the global burden of mental and substance use disorders in children and youth. Psychol Med 2015 May;45(7):1551-1563 [FREE Full text] [doi: 10.1017/S0033291714002888] [Medline: 25534496]
9. Findlay L. Depression and suicidal ideation among Canadians aged 15 to 24. Health Rep 2017 Jan 18;28(1):3-11 [FREE Full text] [Medline: 28098916]
10. Clement S, Schauman O, Graham T, Maggioni F, Evans-Lacko S, Bezborodovs N, et al. What is the impact of mental health-related stigma on help-seeking? A systematic review of quantitative and qualitative studies. Psychol Med 2015 Jan;45(1):11-27. [doi: 10.1017/S0033291714000129] [Medline: 24569086]
11. Nearchou FA, Bird N, Costello A, Duggan S, Gilroy J, Long R, et al. Personal and perceived public mental-health stigma as predictors of help-seeking intentions in adolescents. J Adolesc 2018 Jul;66:83-90. [doi: 10.1016/j.adolescence.2018.05.003] [Medline: 29800758]
12. MacKinnon N, Colman I. Factors associated with suicidal thought and help-seeking behaviour in transition-aged youth versus adults. Can J Psychiatry 2016 Dec;61(12):789-796 [FREE Full text] [doi: 10.1177/0706743716667417] [Medline: 27578771]
13. Townsend E. Time to take self-harm in young people seriously. Lancet Psychiatry 2019 Apr;6(4):279-280 [FREE Full text] [doi: 10.1016/S2215-0366(19)30101-4] [Medline: 30879973]
14. Fleming T, Merry S, Stasiak K, Hopkins S, Patolo T, Ruru S, et al. The importance of user segmentation for designing digital therapy for adolescent mental health: findings from scoping processes. JMIR Ment Health 2019 May 8;6(5):e12656 [FREE Full text] [doi: 10.2196/12656] [Medline: 31066705]
15. Davey CG, McGorry PD. Early intervention for depression in young people: a blind spot in mental health care. Lancet Psychiatry 2019 Mar;6(3):267-272. [doi: 10.1016/s2215-0366(18)30292-x]
16. Price M, Yuen EK, Goetter EM, Herbert JD, Forman EM, Acierno R, et al. mHealth: a mechanism to deliver more accessible, more effective mental health care. Clin Psychol Psychother 2014;21(5):427-436 [FREE Full text] [doi: 10.1002/cpp.1855] [Medline: 23918764]
17. Chandrashekar P. Do mental health mobile apps work: evidence and recommendations for designing high-efficacy mental health mobile apps. Mhealth 2018;4:6 [FREE Full text] [doi: 10.21037/mhealth.2018.03.02] [Medline: 29682510]
18. Aschbrenner KA, Naslund JA, Tomlinson EF, Kinney A, Pratt SI, Brunette MF. Adolescents' use of digital technologies and preferences for mobile health coaching in public mental health settings. Front Public Health 2019;7:178 [FREE Full text] [doi: 10.3389/fpubh.2019.00178] [Medline: 31312629]
19. Fedele DA, Cushing CC, Fritz A, Amaro CM, Ortega A. Mobile health interventions for improving health outcomes in youth: a meta-analysis. JAMA Pediatr 2017 May 1;171(5):461-469 [FREE Full text] [doi: 10.1001/jamapediatrics.2017.0042] [Medline: 28319239]

20. Mar MY, Neilson EK, Torchalla I, Werker GR, Laing A, Krausz M. Exploring e-mental health preferences of generation Y. J Technol Hum Serv 2014 Nov 26;32(4):312-327. [doi: 10.1080/15228835.2014.943457]
21. Seko Y, Kidd S, Wiljer D, McKenzie K. Youth mental health interventions via mobile phones: a scoping review. Cyberpsychol Behav Soc Netw 2014 Sep;17(9):591-602. [doi: 10.1089/cyber.2014.0078] [Medline: 25007383]
22. Lattie EG, Adkins EC, Winquist N, Stiles-Shields C, Wafford QE, Graham AK. Digital mental health interventions for depression, anxiety, and enhancement of psychological well-being among college students: systematic review. J Med Internet Res 2019 Jul 22;21(7):e12869 [FREE Full text] [doi: 10.2196/12869] [Medline: 31333198]
23. Torous J, Nicholas J, Larsen ME, Firth J, Christensen H. Clinical review of user engagement with mental health smartphone apps: evidence, theory and improvements. Evid Based Ment Health 2018 Aug;21(3):116-119. [doi: 10.1136/eb-2018-102891] [Medline: 29871870]
24. Yardley L, Choudhury T, Patrick K, Michie S. Current issues and future directions for research into digital behavior change interventions. Am J Prev Med 2016 Nov;51(5):814-815. [doi: 10.1016/j.amepre.2016.07.019] [Medline: 27745680]
25. Pham Q, Graham G, Carrion C, Morita PP, Seto E, Stinson JN, et al. A library of analytic indicators to evaluate effective engagement with consumer mhealth apps for chronic conditions: scoping review. JMIR Mhealth Uhealth 2019 Jan 18;7(1):e11941 [FREE Full text] [doi: 10.2196/11941] [Medline: 30664463]
26. Wiljer D, Abi-Jaoude A, Johnson A, Ferguson G, Sanches M, Levinson A, et al. Enhancing self-efficacy for help-seeking among transition-aged youth in postsecondary settings with mental health and/or substance use concerns, using crowd-sourced online and mobile technologies: the thought spot protocol. JMIR Res Protoc 2016 Nov 4;5(4):e201 [FREE Full text] [doi: 10.2196/resprot.6446] [Medline: 27815232]
27. van Heerwaarden N, Ferguson G, Abi-Jaoude A, Johnson A, Hollenberg E, Chaim G, et al. The optimization of an ehealth solution (thought spot) with transition-aged youth in postsecondary settings: participatory design research. J Med Internet Res 2018 Mar 6;20(3):e79 [FREE Full text] [doi: 10.2196/jmir.8102] [Medline: 29510970]
28. Kaur A, Isaranuwatchai W, Jaffer A, Ferguson G, Abi-Jaoude A, Johnson A, et al. A web- and mobile-based map of mental health resources for postsecondary students (thought spot): protocol for an economic evaluation. JMIR Res Protoc 2018 Mar 29;7(3):e83 [FREE Full text] [doi: 10.2196/resprot.9478] [Medline: 29599106]
29. Sennah S, Shi J, Hollenberg E, Johnson A, Ferguson G, Abi-Jaoudé A, et al. Thought spot: embedding usability testing into the development cycle. Stud Health Technol Inform 2019;257:375-381. [Medline: 30741226]
30. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res 2005 Feb;8(1):19-32. [doi: 10.1080/1364557032000119616]
31. Xu W, Liu Y. mHealthapps: a repository and database of mobile health apps. JMIR Mhealth Uhealth 2015 Mar 18;3(1):e28 [FREE Full text] [doi: 10.2196/mhealth.4026] [Medline: 25786060]
32. McHugh ML. Interrater reliability: the kappa statistic. Biochem Med (Zagreb) 2012;22(3):276-282 [FREE Full text] [doi: 10.1016/j.jocd.2012.03.005. 5] [Medline: 23092060]
33. Wallace BC, Small K, Brodley C, Lau J, Trikalinos T. Deploying an Interactive Machine Learning System in an Evidence-Based Practice Center: Abstrackr. In: Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium. 2012 Presented at: IHI'12; January 28-30, 2012; New York, USA p. 819-824. [doi: 10.1145/2110363.2110464]
34. Cochrane Public Health. Data Extraction and Assessment Template URL: https://ph.cochrane.org/sites/ph.cochrane.org/files/public/uploads/CPHG%20Data%20extraction%20template_0.docx [accessed 2019-08-15]
35. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Fifth Edition. Washington, DC: American Psychiatric Association Publication; 2013.
36. World Health Organization. 2018. Classification of Digital Health Interventions v1.0: A Shared Language to Describe the Uses of Digital Technology for Health URL: https://www.who.int/reproductivehealth/publications/mhealth/classification-digital-health-interventions/en/ [accessed 2019-08-15]
37. Hsieh H, Shannon SE. Three approaches to qualitative content analysis. Qual Health Res 2005 Nov;15(9):1277-1288. [doi: 10.1177/1049732305276687] [Medline: 16204405]
38. Moher D, Liberati A, Tetzlaff J, Altman DG, PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 2009 Jul 21;6(7):e1000097 [FREE Full text] [doi: 10.1371/journal.pmed.1000097] [Medline: 19621072]
39. Bewick BM, Trusler K, Mulhern B, Barkham M, Hill AJ. The feasibility and effectiveness of a web-based personalised feedback and social norms alcohol intervention in UK university students: a randomised control trial. Addict Behav 2008 Sep;33(9):1192-1198. [doi: 10.1016/j.addbeh.2008.05.002] [Medline: 18554819]
40. van Voorhees BW, Fogel J, Reinecke MA, Gladstone T, Stuart S, Gollan J, et al. Randomized clinical trial of an internet-based depression prevention program for adolescents (Project CATCH-IT) in primary care: 12-week outcomes. J Dev Behav Pediatr 2009 Feb;30(1):23-37 [FREE Full text] [doi: 10.1097/DBP.0b013e3181966c2a] [Medline: 19194326]
41. Christensen H, Griffiths KM, Mackinnon AJ, Kalia K, Batterham PJ, Kenardy J, et al. Protocol for a randomised controlled trial investigating the effectiveness of an online ehealth application for the prevention of generalised anxiety disorder. BMC Psychiatry 2010 Mar 21;10:25 [FREE Full text] [doi: 10.1186/1471-244X-10-25] [Medline: 20302678]

42. Shandley K, Austin D, Klein B, Kyrios M. An evaluation of 'reach out central': an online gaming program for supporting the mental health of young people. Health Educ Res 2010 Aug;25(4):563-574. [doi: 10.1093/her/cyq002] [Medline: 20150530]
43. Paschall MJ, Antin T, Ringwalt CL, Saltz RF. Evaluation of an internet-based alcohol misuse prevention course for college freshmen: findings of a randomized multi-campus trial. Am J Prev Med 2011 Sep;41(3):300-308 [FREE Full text] [doi: 10.1016/j.amepre.2011.03.021] [Medline: 21855745]
44. Jacobi C, Völker U, Trockel MT, Taylor CB. Effects of an internet-based intervention for subthreshold eating disorders: a randomized controlled trial. Behav Res Ther 2012 Feb;50(2):93-99. [doi: 10.1016/j.brat.2011.09.013] [Medline: 22137366]
45. Stice E, Rohde P, Durant S, Shaw H. A preliminary trial of a prototype internet dissonance-based eating disorder prevention program for young women with body image concerns. J Consult Clin Psychol 2012 Oct;80(5):907-916 [FREE Full text] [doi: 10.1037/a0028016] [Medline: 22506791]
46. Saulsberry A, Marko-Holguin M, Blomeke K, Hinkle C, Fogel J, Gladstone T, et al. Randomized clinical trial of a primary care internet-based intervention to prevent adolescent depression: one-year outcomes. J Can Acad Child Adolesc Psychiatry 2013 May;22(2):106-117 [FREE Full text] [Medline: 23667356]
47. Deady M, Teesson M, Kay-Lambkin F, Mills KL. Evaluating a brief, internet-based intervention for co-occurring depression and problematic alcohol use in young people: protocol for a randomized controlled trial. JMIR Res Protoc 2014 Feb 27;3(1):e6 [FREE Full text] [doi: 10.2196/resprot.3192] [Medline: 24583824]
48. Richards D, Timulak L, Doherty G, Sharry J, McLoughlin O, Rashleigh C, et al. Low-intensity internet-delivered treatment for generalized anxiety symptoms in routine care: protocol for a randomized controlled trial. Trials 2014 Apr 27;15:145 [FREE Full text] [doi: 10.1186/1745-6215-15-145] [Medline: 24767603]
49. Kass AE, Trockel M, Safer DL, Sinton MM, Cunning D, Rizk MT, et al. Internet-based preventive intervention for reducing eating disorder risk: a randomized controlled trial comparing guided with unguided self-help. Behav Res Ther 2014 Dec;63:90-98 [FREE Full text] [doi: 10.1016/j.brat.2014.09.010] [Medline: 25461783]
50. Nahum M, Fisher M, Loewy R, Poelke G, Ventura J, Nuechterlein KH, et al. A novel, online social cognitive training program for young adults with schizophrenia: a pilot study. Schizophr Res Cogn 2014 Mar 1;1(1):e11-e19 [FREE Full text] [doi: 10.1016/j.scog.2014.01.003] [Medline: 25267937]
51. Saekow J, Jones M, Gibbs E, Jacobi C, Fitzsimmons-Craft EE, Wilfley D, et al. StudentBodies-eating disorders: a randomized controlled trial of a coached online intervention for subclinical eating disorders. Internet Interv 2015 Nov;2(4):419-428. [doi: 10.1016/j.invent.2015.10.004]
52. Morris RR, Schueller SM, Picard RW. Efficacy of a web-based, crowdsourced peer-to-peer cognitive reappraisal platform for depression: randomized controlled trial. J Med Internet Res 2015 Mar 30;17(3):e72 [FREE Full text] [doi: 10.2196/jmir.4167] [Medline: 25835472]
53. Perry Y, Calear AL, Mackinnon A, Batterham PJ, Licinio J, King C, et al. Trial for the prevention of depression (TriPoD) in final-year secondary students: study protocol for a cluster randomised controlled trial. Trials 2015 Oct 12;16:451 [FREE Full text] [doi: 10.1186/s13063-015-0929-1] [Medline: 26458896]
54. Rickhi B, Kania-Richmond A, Moritz S, Cohen J, Paccagnan P, Dennis C, et al. Evaluation of a spirituality informed e-mental health tool as an intervention for major depressive disorder in adolescents and young adults-a randomized controlled pilot trial. BMC Complement Altern Med 2015 Dec 24;15:450 [FREE Full text] [doi: 10.1186/s12906-015-0968-x] [Medline: 26702639]
55. Richards K, Marko-Holguin M, Fogel J, Anker L, Ronayne J, van Voorhees BW. Randomized clinical trial of an internet-based intervention to prevent adolescent depression in a primary care setting (Catch-It): 2.5-year outcomes. J Evid Based Psychother 2016 Sep;16(2):113-134 [FREE Full text] [Medline: 30345428]
56. Bidargaddi N, Musiat P, Winsall M, Vogl G, Blake V, Quinn S, et al. Efficacy of a web-based guided recommendation service for a curated list of readily available mental health and well-being mobile apps for young people: randomized controlled trial. J Med Internet Res 2017 May 12;19(5):e141 [FREE Full text] [doi: 10.2196/jmir.6775] [Medline: 28500020]
57. Lattie EG, Duffecy JL, Mohr DC, Kashima K. Development and evaluation of an online mental health program for medical students. Acad Psychiatry 2017 Oct;41(5):642-645 [FREE Full text] [doi: 10.1007/s40596-017-0726-0] [Medline: 28536989]
58. Tighe J, Shand F, Ridani R, Mackinnon A, de la Mata N, Christensen H. Ibobbly mobile health intervention for suicide prevention in Australian indigenous youth: a pilot randomised controlled trial. BMJ Open 2017 Jan 27;7(1):e013518 [FREE Full text] [doi: 10.1136/bmjopen-2016-013518] [Medline: 28132007]
59. Podina IR, Fodor LA, Cosmoiu A, Boian R. An evidence-based gamified mHealth intervention for overweight young adults with maladaptive eating habits: study protocol for a randomized controlled trial. Trials 2017 Dec 12;18(1):592 [FREE Full text] [doi: 10.1186/s13063-017-2340-6] [Medline: 29233169]
60. Lima-Serrano M, Martínez-Montilla JM, Lima-Rodríguez JS, Mercken L, de Vries H. Design, implementation and evaluation of a web-based computer-tailored intervention to prevent binge drinking in adolescents: study protocol. BMC Public Health 2018 Apr 4;18(1):449 [FREE Full text] [doi: 10.1186/s12889-018-5346-4] [Medline: 29618331]
61. Logsdon MC, Myers J, Rushton J, Gregg JL, Josephson AM, Davis DW, et al. Efficacy of an internet-based depression intervention to improve rates of treatment in adolescent mothers. Arch Womens Ment Health 2018 Jun;21(3):273-285 [FREE Full text] [doi: 10.1007/s00737-017-0804-z] [Medline: 29260321]

62. Harrer M, Adam SH, Fleischmann RJ, Baumeister H, Auerbach R, Bruffaerts R, et al. Effectiveness of an internet- and app-based intervention for college students with elevated stress: randomized controlled trial. J Med Internet Res 2018 Apr 23;20(4):e136 [FREE Full text] [doi: 10.2196/jmir.9293] [Medline: 29685870]
63. Schlosser DA, Campellone TR, Truong B, Etter K, Vergani S, Komaiko K, et al. Efficacy of PRIME, a mobile app intervention designed to improve motivation in young people with schizophrenia. Schizophr Bull 2018 Aug 20;44(5):1010-1020 [FREE Full text] [doi: 10.1093/schbul/sby078] [Medline: 29939367]
64. Karyotaki E, Klein AM, Riper H, Wit LD, Krijnen L, Bol E, et al. Examining the effectiveness of a web-based intervention for symptoms of depression and anxiety in college students: study protocol of a randomised controlled trial. BMJ Open 2019 May 14;9(5):e028739 [FREE Full text] [doi: 10.1136/bmjopen-2018-028739] [Medline: 31092668]
65. Hides L, Dingle G, Quinn C, Stoyanov SR, Zelenko O, Tjondronegoro D, et al. Efficacy and outcomes of a music-based emotion regulation mobile app in distressed young people: randomized controlled trial. JMIR Mhealth Uhealth 2019 Jan 16;7(1):e11482 [FREE Full text] [doi: 10.2196/11482] [Medline: 30664457]
66. Palacios JE, Richards D, Palmer R, Coudray C, Hofmann SG, Palmieri PA, et al. Supported internet-delivered cognitive behavioral therapy programs for depression, anxiety, and stress in university students: open, non-randomised trial of acceptability, effectiveness, and satisfaction. JMIR Ment Health 2018 Dec 14;5(4):e11467 [FREE Full text] [doi: 10.2196/11467] [Medline: 30552076]
67. Wilksch SM, O'Shea A, Taylor CB, Wilfley D, Jacobi C, Wade TD. Online prevention of disordered eating in at-risk young-adult women: a two-country pragmatic randomized controlled trial. Psychol Med 2018 Sep;48(12):2034-2044 [FREE Full text] [doi: 10.1017/S0033291717003567] [Medline: 29233196]
68. Brunette MF, Ferron JC, Robinson D, Coletti D, Geiger P, Devitt T, et al. Brief web-based interventions for young adult smokers with severe mental illnesses: a randomized, controlled pilot study. Nicotine Tob Res 2018 Sep 4;20(10):1206-1214 [FREE Full text] [doi: 10.1093/ntr/ntx190] [Medline: 29059417]
69. Eustis EH, Hayes-Skelton SA, Orsillo SM, Roemer L. Surviving and thriving during stress: a randomized clinical trial comparing a brief web-based therapist-assisted acceptance-based behavioral intervention versus waitlist control for college students. Behav Ther 2018 Nov;49(6):889-903. [doi: 10.1016/j.beth.2018.05.009] [Medline: 30316488]
70. Alvarez-Jimenez M, Bendall S, Lederman R, Wadley G, Chinnery G, Vargas S, et al. On the HORYZON: moderated online social therapy for long-term recovery in first episode psychosis. Schizophr Res 2013 Jan;143(1):143-149. [doi: 10.1016/j.schres.2012.10.009] [Medline: 23146146]
71. Rice S, Gleeson J, Davey C, Hetrick S, Parker A, Lederman R, et al. Moderated online social therapy for depression relapse prevention in young people: pilot study of a 'next generation' online intervention. Early Interv Psychiatry 2018 Aug;12(4):613-625. [doi: 10.1111/eip.12354] [Medline: 27311581]
72. Schlosser D, Campellone T, Kim D, Truong B, Vergani S, Ward C, et al. Feasibility of PRIME: a cognitive neuroscience-informed mobile app intervention to enhance motivated behavior and improve quality of life in recent onset schizophrenia. JMIR Res Protoc 2016 Apr 28;5(2):e77 [FREE Full text] [doi: 10.2196/resprot.5450] [Medline: 27125771]
73. Deady M, Mills KL, Teesson M, Kay-Lambkin F. An online intervention for co-occurring depression and problematic alcohol use in young people: primary outcomes from a randomized controlled trial. J Med Internet Res 2016 Mar 23;18(3):e71 [FREE Full text] [doi: 10.2196/jmir.5178] [Medline: 27009465]
74. Stallman HM, Kavanagh DJ. Development of an internet intervention to promote wellbeing in college students. Aust Psychol 2016 Aug 28;53(1):60-67. [doi: 10.1111/ap.12246]
75. Juniar D, van Ballegooijen W, Karyotaki E, van Schaik A, Passchier J, Heber E, et al. Web-based stress management program for university students in Indonesia: systematic cultural adaptation and protocol for a feasibility study. JMIR Res Protoc 2019 Jan 25;8(1):e11493 [FREE Full text] [doi: 10.2196/11493] [Medline: 30681970]
76. Backman A, Mellblom A, Norman-Claesson E, Keith-Bodros G, Frostvittra M, Bölte S, et al. Internet-delivered psychoeducation for older adolescents and young adults with autism spectrum disorder (SCOPE): an open feasibility study. Res Autism Spec Dis 2018 Oct;54:51-64. [doi: 10.1016/j.rasd.2018.07.001]
77. Bailey JV, Pavlou M, Copas A, McCarthy O, Carswell K, Rait G, et al. The Sexunzipped trial: optimizing the design of online randomized controlled trials. J Med Internet Res 2013 Dec 11;15(12):e278 [FREE Full text] [doi: 10.2196/jmir.2668] [Medline: 24334216]
78. Gladstone T, Marko-Holguin M, Henry J, Fogel J, Diehl A, van Voorhees BW. Understanding adolescent response to a technology-based depression prevention program. J Clin Child Adolesc Psychol 2014;43(1):102-114 [FREE Full text] [doi: 10.1080/15374416.2013.850697] [Medline: 24245935]
79. Levin ME, Pistorello J, Seeley JR, Hayes SC. Feasibility of a prototype web-based acceptance and commitment therapy prevention program for college students. J Am Coll Health 2014;62(1):20-30 [FREE Full text] [doi: 10.1080/07448481.2013.843533] [Medline: 24313693]
80. Lillevoll KR, Vangberg HC, Griffiths KM, Waterloo K, Eisemann MR. Uptake and adherence of a self-directed internet-based mental health intervention with tailored e-mail reminders in senior high schools in Norway. BMC Psychiatry 2014 Jan 21;14:14 [FREE Full text] [doi: 10.1186/1471-244X-14-14] [Medline: 24443820]

81. Witkiewitz K, Desai SA, Bowen S, Leigh BC, Kirouac M, Larimer ME. Development and evaluation of a mobile intervention for heavy drinking and smoking among college students. Psychol Addict Behav 2014 Sep;28(3):639-650 [FREE Full text] [doi: 10.1037/a0034747] [Medline: 25000269]
82. Kruger JR, Kim P, Iyer V, Marko-Holguin M, Fogel J, DeFrino D, et al. Evaluation of protective and vulnerability factors for depression following an internet-based intervention to prevent depression in at-risk adolescents. Int J Ment Health Promot 2017 Apr 19;19(2):69-84. [doi: 10.1080/14623730.2017.1308264]
83. van Rosmalen-Nooijens K, Lo Fo Wong S, Prins J, Lagro-Janssen T. Young people, adult worries: randomized controlled trial and feasibility study of the internet-based self-support method 'feel the vibe' for adolescents and young adults exposed to family violence. J Med Internet Res 2017 Jun 12;19(6):e204 [FREE Full text] [doi: 10.2196/jmir.6004] [Medline: 28606893]
84. Jaffe AE, Bountress KE, Metzger IW, Maples-Keller JL, Pinsky HT, George WH, et al. Student engagement and comfort during a web-based personalized feedback intervention for alcohol and sexual assault. Addict Behav 2018 Jul;82:23-27 [FREE Full text] [doi: 10.1016/j.addbeh.2018.02.020] [Medline: 29477903]
85. Takahashi K, Takada K, Hirao K. Feasibility and preliminary efficacy of a smartphone application intervention for subthreshold depression. Early Interv Psychiatry 2019 Feb;13(1):133-136. [doi: 10.1111/eip.12540] [Medline: 29356332]
86. Sagon AL, Danitz SB, Suvak MK, Orsillo SM. The mindful way through the semester: evaluating the feasibility of delivering an acceptance-based behavioral program online. J Contextual Behav Sci 2018 Jul;9:36-44. [doi: 10.1016/j.jcbs.2018.06.004]
87. Moir F, Fernando AT, Kumar S, Henning M, Moyes SA, Elley CR. Computer assisted learning for the mind (CALM): the mental health of medical students and their use of a self-help website. N Z Med J 2015 Mar 27;128(1411):51-58. [Medline: 25820503]
88. Google Analytics. 2019. URL: https://analytics.google.com [accessed 2019-08-15]
89. Moffitt TE, Caspi A. Psychiatry's opportunity to prevent the rising burden of age-related disease. JAMA Psychiatry 2019 May 1;76(5):461-462. [doi: 10.1001/jamapsychiatry.2019.0037] [Medline: 30916735]
90. Gunnell D, Kidger J, Elvidge H. Adolescent mental health in crisis. Br Med J 2018 Jun 19;361:k2608. [doi: 10.1136/bmj.k2608] [Medline: 29921659]
91. Grist R, Porter J, Stallard P. Mental health mobile apps for preadolescents and adolescents: a systematic review. J Med Internet Res 2017 May 25;19(5):e176 [FREE Full text] [doi: 10.2196/jmir.7332] [Medline: 28546138]
92. Onnela J, Rauch SL. Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. Neuropsychopharmacology 2016 Jun;41(7):1691-1696 [FREE Full text] [doi: 10.1038/npp.2016.7] [Medline: 26818126]
93. Insel TR. Digital phenotyping: technology for a new science of behavior. J Am Med Assoc 2017 Oct 03;318(13):1215-1216. [doi: 10.1001/jama.2017.11295] [Medline: 28973224]
94. Torous J, Gershon A, Hays R, Onnela J, Baker JT. Digital phenotyping for the busy psychiatrist: clinical implications and relevance. Psych Ann 2019 May 1;49(5):196-201. [doi: 10.3928/00485713-20190417-01]
95. Torous J, Keshavan M, Gutheil T. Promise and perils of digital psychiatry. Asian J Psychiatr 2014 Aug;10:120-122. [doi: 10.1016/j.ajp.2014.06.006] [Medline: 25042968]
96. Short CE, de Smet A, Woods C, Williams SL, Maher C, Middelweerd A, et al. Measuring engagement in ehealth and mhealth behavior change interventions: viewpoint of methodologies. J Med Internet Res 2018 Nov 16;20(11):e292 [FREE Full text] [doi: 10.2196/jmir.9397] [Medline: 30446482]
97. Yardley L, Spring BJ, Riper H, Morrison LG, Crane DH, Curtis K, et al. Understanding and promoting effective engagement with digital behavior change interventions. Am J Prev Med 2016 Nov;51(5):833-842. [doi: 10.1016/j.amepre.2016.06.015] [Medline: 27745683]
98. Vedel I, Lapointe L, Lussier M, Richard C, Goudreau J, Lalonde L, et al. Healthcare professionals' adoption and use of a clinical information system (CIS) in primary care: insights from the Da Vinci study. Int J Med Inform 2012 Feb;81(2):73-87. [doi: 10.1016/j.ijmedinf.2011.11.002] [Medline: 22192460]
99. Ash JS, Bates DW. Factors and forces affecting EHR system adoption: report of a 2004 ACMI discussion. J Am Med Inform Assoc 2005;12(1):8-12 [FREE Full text] [doi: 10.1197/jamia.M1684] [Medline: 15492027]
100. Strudwick G. Predicting nurses' use of healthcare technology using the technology acceptance model: an integrative review. Comput Inform Nurs 2015 May;33(5):189-98; quiz E1. [doi: 10.1097/CIN.0000000000000142] [Medline: 25974361]
101. Price M, Lau F. The clinical adoption meta-model: a temporal meta-model describing the clinical adoption of health information systems. BMC Med Inform Decis Mak 2014 May 29;14:43 [FREE Full text] [doi: 10.1186/1472-6947-14-43] [Medline: 24884588]
102. Hall GE. A Developmental Conceptualization of the Adoption Process Within Educational Institutions. Texas, USA: Research and Development Center for Teacher Education; 1973.
103. Rogers EM. Diffusion of Innovations. New York, USA: Free Press; 1995.
104. Singh K, Meyer SR, Westfall JM. Consumer-facing data, information, and tools: self-management of health in the digital age. Health Aff (Millwood) 2019 Mar;38(3):352-358. [doi: 10.1377/hlthaff.2018.05404] [Medline: 30830832]
105. Torous J, Wisniewski H, Liu G, Keshavan M. Mental health mobile phone app usage, concerns, and benefits among psychiatric outpatients: comparative survey study. JMIR Ment Health 2018 Nov 16;5(4):e11715 [FREE Full text] [doi: 10.2196/11715] [Medline: 30446484]

106. Wartella E, Rideout V, Montague H, Beaudoin-Ryan L, Lauricella A. Teens, health and technology: a national survey. Media Comm 2016 Jun 16;4(3):13. [doi: 10.17645/mac.v4i3.515]
107. McCurdie T, Taneva S, Casselman M, Yeung M, McDaniel C, Ho W, et al. mHealth consumer apps: the case for user-centered design. Biomed Instrum Technol 2012;Suppl:49-56. [doi: 10.2345/0899-8205-46.s2.49] [Medline: 23039777]
108. Cheng VW, Davenport T, Johnson D, Vella K, Hickie IB. Gamification in apps and technologies for improving mental health and well-being: systematic review. JMIR Ment Health 2019 Jun 26;6(6):e13717 [FREE Full text] [doi: 10.2196/13717] [Medline: 31244479]
109. Fleming T, Bavin L, Lucassen M, Stasiak K, Hopkins S, Merry S. Beyond the trial: systematic review of real-world uptake and engagement with digital self-help interventions for depression, low mood, or anxiety. J Med Internet Res 2018 Jun 6;20(6):e199 [FREE Full text] [doi: 10.2196/jmir.9275] [Medline: 29875089]
110. Gupta SK. Intention-to-treat concept: a review. Perspect Clin Res 2011 Jul;2(3):109-112 [FREE Full text] [doi: 10.4103/2229-3485.83221] [Medline: 21897887]
111. Torous J, Staples P, Slaters L, Adams J, Sandoval L, Onnela JP, et al. Characterizing smartphone engagement for schizophrenia: results of a naturalist mobile health study. Clin Schizophr Relat Psychoses 2017 Aug 4 epub ahead of print. [doi: 10.3371/CSRP.JTPS.071317] [Medline: 28777029]
112. Connolly SL, Miller CJ, Koenig CJ, Zamora KA, Wright PB, Stanley RL, et al. Veterans' attitudes toward smartphone app use for mental health care: qualitative study of rurality and age differences. JMIR Mhealth Uhealth 2018 Aug 22;6(8):e10748 [FREE Full text] [doi: 10.2196/10748] [Medline: 30135050]
113. Chaffey D, Patron M. From web analytics to digital marketing optimization: increasing the commercial value of digital analytics. J Direct Data Digit Mark Pract 2012 Aug 8;14(1):30-45. [doi: 10.1057/dddmp.2012.20]
114. Bakken S. The importance of consumer-and patient-oriented perspectives in biomedical and health informatics. J Am Med Inform Assoc 2019 Jul 1;26(7):583-584. [doi: 10.1093/jamia/ocz073] [Medline: 31192361]

## Abbreviations

**eHealth:** electronic health
**MEDLINE:** Medical Literature Analysis and Retrieval System
**mHealth:** mobile health
**RCT:** randomized controlled trial
**WHO:** World Health Organization

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Original Paper

# Acceptability and Utility of an Open-Access, Online Single-Session Intervention Platform for Adolescent Mental Health

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## Abstract

**Background:** Many youths with mental health needs are unable to access care. Single-session interventions (SSIs) have helped reduce youth psychopathology across multiple trials, promising to broaden access to effective, low-intensity supports. Online, self-guided SSIs may be uniquely scalable, particularly if they are freely available for as-needed use. However, the acceptability of online SSI and their efficacy have remained unexamined outside of controlled trials, and their practical utility is poorly understood.

**Objective:** We evaluated the perceived acceptability and proximal effects of Project YES (Youth Empowerment & Support), an open-access platform offering three online SSIs for youth internalizing distress.

**Methods:** After selecting one of three SSIs to complete, participants (ages 11-17 years) reported pre- and post-SSI levels of clinically relevant outcomes that SSIs may target (eg, hopelessness, self-hate) and perceived SSI acceptability. User-pattern variables, demographics, and depressive symptoms were collected to characterize youths engaging with YES.

**Results:** From September 2019 through March 2020, 694 youths accessed YES, 539 began, and 187 completed a 30-minute, self-guided SSI. SSI completers reported clinically elevated depressive symptoms, on average, and were diverse on several dimensions (53.75% non-white; 78.10% female; 43.23% sexual minorities). Regardless of SSI selection, completers reported pre- to post-program reductions in hopelessness ($d_{av}$=0.53; $d_z$=0.71), self-hate ($d_{av}$=0.32; $d_z$=0.61), perceived control ($d_{av}$=0.60; $d_z$=0.72) and agency ($d_{av}$=0.39; $d_z$=0.50). Youths rated all SSIs as acceptable (eg, enjoyable, likely to help peers).

**Conclusions:** Results support the perceived acceptability and utility of open-access, free-of-charge SSIs for youth experiencing internalizing distress.

**Trial Registration:** Open Science Framework; osf.io/e52p3

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**KEYWORDS**

internet intervention; online interventions; youth; mental health; adolescent; depression; single-session intervention; intervention

## Introduction

The persistent unmet need for youth mental health services, combined with the ubiquity of internet-equipped devices, has fueled a surge of interest in digital mental health interventions. Despite decades of progress in the identification of evidence-supported psychosocial treatments, myriad barriers—both systemic (high costs, transportation challenges) and internal (stigma, preferences for self-help)—prevent up to 80% of youth from accessing needed care [1,2]. The notion of low-cost, self-guided digital interventions thus appeals to researchers, providers, and clients alike. Indeed, mental healthcare apps are downloaded by millions of users annually [3,4], and a vast majority of adolescents in the United States have access to internet-equipped smartphones (95%) and computers (88%) [5]. These realities create opportunities for youth with no accessible alternatives to engage with digital supports.

Randomized trials suggest the promise of internet- and smartphone-based youth mental health tools [6-10]. However, formal clinical trial outcomes may not reflect the utility or usability of digital supports in naturalistic contexts. First, few evidence-based digital interventions developed for clinical trials are publicly accessible [11], and those that are accessible attract far fewer users than commercially popular but untested alternatives (eg, Headspace) [12]. Indeed, the most frequently downloaded mental health apps include *few* to *no* treatment elements found in empirically supported psychotherapies [13,14]. Second, digital intervention attrition rates differ markedly in clinical trials and "real-world" contexts. In a review of digital self-help tools, including apps and internet-based programs for depression and anxiety, completion rates for programs in clinical trials were 44%-99%. In contrast, completion rates for the same programs in naturalistic, non-research settings—where participants received no incentives for program engagement—were 1%-28% [15].

Overall, daily usage rates for mental health apps hovers at just 4% (based on rates of opening a previously downloaded program) [7]. Reasons for low engagement in youth-directed mental health apps include lack of perceived program value, limits on program accessibility (eg, within-program fees, limits on 24/7 access), and poor user experience (eg, high demands on users' time) [4,16]. Thus, a need exists for digital mental health supports that (1) include evidence-based content, established in well-controlled trials; (2) show acceptability in naturalistic contexts (ie, outside of formal trials); (3) minimize demands on users' time, given the high likelihood of accessing a digital intervention only once; and (4) are free of access barriers, such as program costs.

Single-session interventions (SSIs)—structured interventions, including *one* component of empirically supported treatments and requiring *one* encounter with a provider or program—could dramatically improve the acceptability and accessibility of digital mental health tools. Overall, SSI effects on youth psychopathology are slightly smaller than those observed for youth treatments lasting an average of 16 sessions ($g$=0.32 for single-session interventions [17], versus $g$=0.46 for multi-session interventions [17,18]. However, their brevity and flexible format magnify their potential public health impact [19]. Additionally, across placebo-controlled trials, self-administered online SSIs have reduced youth depression across 4-9 months in high-symptom and community youth samples [20-22]. These findings suggest the untapped potential of online SSIs to improve youth access to effective support.

In principle, online SSIs might overcome many challenges typical of traditional digital mental health tools. They are completable within one sitting, minimizing engagement burdens on users, and many are cost-free, publicly accessible, and include evidence-based intervention components. However, there have been no formal evaluations of the acceptability of online SSIs outside of controlled clinical trials. To gauge the promise and challenges to realizing the potential of online SSIs to benefit youth mental health, we must systematically evaluate usage patterns, perceived acceptability, and the short-term effects of online SSIs in naturalistic contexts.

Toward this goal, we conducted an open-access program evaluation of online SSIs for adolescent mental health, Project YES (Youth Empowerment & Support) [23], to evaluate the acceptability and initial effects of three free-of-charge, publicly available web-based SSIs for adolescent internalizing distress. In line with SSI design recommendations, each of these three SSIs was intended to target and strengthen *adaptive beliefs* about the self and the world that have been shown to predict youth internalizing distress.

The first SSI, Project Personality, teaches how and why people's traits—including their symptoms—are malleable rather than fixed [20]. Project Personality aims to strengthen adolescents' *perceived control* over their behavior and emotions while *reducing hopelessness* regarding a positive future change. Low perceived control and elevated hopelessness consistently predict the course and severity of youth internalizing problems [24-28]. Further, both perceived control and hopelessness are modifiable via brief intervention, making them ideal proximal SSI targets. In a recent placebo-controlled trial, Project Personality significantly improved perceived control over emotions and behavior in adolescents characterized as high-symptom [15], and larger proximal increases in perceived control following Project Personality predicted greater reductions in internalizing symptoms over time [29]. Thus, in the context of Project YES, we assessed Project Personality's link with improvements in perceived control and hopelessness.

The second SSI, Project CARE, teaches how and why one can work towards acting with self-compassion in order to reduce self-hate systematically [30]. Self-hate and closely related constructs (ie, self-criticism) are linked with current and future internalizing problems in both youths and adults [31-35]. Preliminary evidence also suggests negative perceptions of the self, including self-hate, are *modifiable* through self-administered interventions as brief as 5-11 minutes [36-39]. Thus, within Project YES, we assessed Project CARE's link with improvements in self-hate.

The third SSI, the ABC Project, is modeled after behavioral activation interventions targeting adolescent depression, which teach that engaging in valued activities can powerfully shape one's mood [30,40]. The construct of *agency*—one's self-perceived ability to initiate and work towards goals—is central to mechanisms thought to underlie behavioral activation for youth depression. Specifically, "agency" references an individual's perceived capacity to (a) set behavioral goals, and (b) maintain or generate motivation to move toward those goals [41]. Behavioral activation for adolescent depression—including a one-session, therapist-delivered program [42]—has produced marked improvements in adolescents' perceived agency and depression symptom severity, relative to control conditions [43-45] Thus, within Project YES, we assessed the ABC Project's link with proximal improvements in agency.

Each 30-minute program was created per a routinely employed SSI design framework, informed by basic social-psychological research and detailed elsewhere [19], wherein youths (1) learn brain science that normalizes each program's core concept; (2)

are treated as "experts" and invited to help researchers learn about youths' perspectives and challenges; (3) synthesize the program's ideas using their own words, while offering advice to peers facing difficulties; (4) hear stories from peers who used the program's content to overcome setbacks. Regardless of SSI selection, youths taking part in YES are invited to offer their "best, anonymous coping advice" to other teens coping with depression or anxiety; each receives the option to share this advice to a public "YES advice center." This feature builds on research suggesting that helping or supporting peers can benefit an individual's sense of self-efficacy, motivation, and psychosocial functioning [46-48].

All YES participants may complete anonymous pre- and post-program assessments of proximal outcomes that may be altered by SSIs (per prior recommendations for evaluating SSI effects; [19]) along with feedback on program acceptability. Using pre-SSI, post-SSI, and user-pattern data collected from YES participants ages 11-17 over 7 months, we investigated the acceptability of YES SSIs among youths, including completion rates and perceptions of each SSI's utility. We also assessed the *immediate effects* of YES SSIs on interrelated and clinically relevant outcomes they are designed to target, each of which relates to youth internalizing problems (agency, perceived control, hopelessness, and self-hate, assessed using both standardized and study-specific metrics). Specifically, we examined usage-pattern variables (eg, SSI selection, SSI completion rates), user characteristics (age-range, sex, gender identity, race/ethnicity, depressive symptoms), and acceptability metrics to gauge *which youths* use YES; *how* and *why* they engage with it; and whether they view YES as valuable, helpful, and user-friendly. We also examined whether proximal, clinically relevant outcomes significantly improved from pre- to post-SSI, both across all YES programs and within each program. This nonexperimental, observational project represents a critical step in understanding the promise of online mental health SSIs, and the challenges to realizing that promise.

## Methods

### Participants

Participants were youths ages 11-17 who took part in YES between September 19, 2019, and March 10, 2020. Participants learned about YES through various channels, including unpaid posts to social media websites (Reddit, Twitter), Instagram advertisements (total costs <$500), or an article published in *Vox* highlighting the authors' research [49]. Social media posts included invitations to participate in an anonymous program evaluation wherein "teens can learn new ways of dealing with stress and help others do the same." Posts linked to the public YES website [23], which includes additional information and a participation link. YES is completable from any internet-equipped device. Before YES was initiated, all procedures were reviewed and deemed "exempt" (as a program evaluation) by the University's Institutional Review Board.

Because YES is anonymous and publicly accessible, no inclusion or exclusion criteria are used (as none are enforceable). Thus, adults and children aged 10 or younger may choose to participate, although the YES website states that programs are meant for youths under age 18—primarily, pre-adolescent and adolescent youth. Within YES, participants are required to report their age range and whether they are adults (>18). Using these data, we limited analyses to our population of interest (youths under age 18).

### Procedures

YES is a non-randomized, exploratory program evaluation; procedures and analyses were preregistered on Open Science Framework [50]. In order to maintain anonymity and minimize access barriers (eg, discomfort disclosing psychological distress, as parents are often unaware of their adolescents' depressive symptoms, including suicidal and morbid ideation, in up to 80% of cases [51,52]), parent permission is not required to participate (waived by the University IRB). After clicking the YES participation link and advancing past a "Project Information" page where agreement to participate is indicated, participants provide non-identifying demographic information; select one of three SSIs to complete; and may then complete pre-SSI questionnaires, the SSI, and post-SSI questionnaires, designed to gauge the SSI's acceptability and short-term effects. Lastly, participants are invited to anonymously share their "best advice for others dealing with depression, anxiety, or stress." They may elect or decline to share their advice in the YES "Advice Center" for others to see.

### Procedural Deviations

There were three minor deviations from the procedures described in our preregistration that warrant mention. First, to minimize participation burdens for those completing pre- and post-SSI questionnaires in project YES, we decided approximately one month into data collection to use only the 3-item "Agency" subscale of the State Hope Scale as opposed to the full 6-item scale; we also used a shortened 3-item version of the Self-Hatred Scale; these three items were formally selected using confirmatory factor analysis in a separate sample of N=246 adolescents from the same age group (see Multimedia Appendix 1). Second, the Self-Hatred Scale used in this study included 6 response options, not 7, as noted in the preregistration, although the anchors are the same as in the initially validated version and as noted in the preregistration. Lastly, we had initially preregistered an exploratory logistic regression to examine whether YES participants' demographic characteristics or symptom levels predicted odds of SSI completion or choice of SSI. Due to high multicollinearity among preregistered predictors (eg, biological sex and gender identity; Variance Inflation Factor >10), results of this test could not be responsibly interpreted; thus, we do not report them in this manuscript. An alternative approach to conducting these analyses was applied, and results are reported in Multimedia Appendix 1.

### Interventions

Each SSI within Project YES is designed according to four primary elements proposed by Schleider and colleagues [19] for self-guided youth mental health SSIs. These elements were drawn from basic social-psychological research, along with qualities common among SSIs that have demonstrated efficacy [19,22,42,53,54]. Each YES SSI (1) uses brain science-based explanation to enhance content credibility; (2) empowers youth to take on an ‘expert’ or ‘helper’ role throughout the program; (3) includes guided writing assignments, often termed “saying-is-believing” or “self-persuasion” exercises, to enhance content internalization and generalization; and (4) includes testimonials from trusted others, such as older peers or scientific experts. A detailed description of these four principles of SSI design is provided elsewhere [19].

Materials for all SSIs in Project YES are publicly available via the Open Science Framework (Project Personality [55], Project CARE [30], and The ABC Project: [40]). All three are 30-minute, self-administered programs. All materials viewed by youths who take part in Project YES are publicly viewable on the Project YES website [23].

### *Project Personality*

This SSI includes an introduction to the brain and a lesson on neuroplasticity; testimonials from older youths who describe their views that traits are malleable; stories by older youths, describing times when they used “growth mindsets” to persevere during social/emotional setbacks; study summaries noting how/why personality can change; and an exercise in which youths write notes to younger students, using scientific information to explain people’s capacity for change. Project Personality has demonstrated effectiveness in several trials [20,21,56].

### *Project CARE*

This SSI includes: an introduction to the science behind why adolescents might think disliking themselves is necessary for success and thus fear self-compassion; scientific evidence and testimonials from other teens that being self-compassionate predicts being more successful socially and academically; evidence-based tips for overcoming common, fear of self-compassion based obstacles to self-compassion in day to day life; and an exercise in which youths write notes to younger students, using scientific information to explain the benefits of using self-kindness.

### *The ABC Project*

This SSI draws from components of behavioral activation. The ABC Project introduces the concept that engaging in value-based activities that build pleasure and accomplishment can combat a sad mood and low self-esteem. It includes psychoeducation about depression, including how behavior shapes feelings and thoughts, walks participants through a life values assessment, where they identify key areas from which they draw enjoyment and meaning, and supports participants in creating an activity hierarchy, where they identify and personalize 3 activities to target for change. Lastly, the ABC Project includes an exercise in which youths write about benefits that might result from engaging in each activity, identify obstacles that might keep them from doing the activities and a strategy for overcoming identified obstacles.

## Measures

### *Demographics*

Participants selected their age bracket (provided in ranges to maintain anonymity: 11 to 13, 14 to 16, 17 to <18), biological sex, gender identity, sexual orientation, and race/ethnicity.

### *Mood and Feelings Questionnaire–Short*

The Mood and Feelings Questionnaire—Short (SMFQ) is a valid, reliable screening tool for depression in youth [57]. Pre-SSI, participants rated their agreement with 13 statements (eg, “I felt lonely”; “I felt miserable or unhappy”; “I felt I was no good anymore”) reflecting thoughts and feelings in the past two weeks on a 3-point Likert scale (0=“not true”; 2=“true”). Internal consistency was α=.92. Note that the SMFQ does not measure suicidal ideation or suicidality, which are not assessed in the context of Project YES.

### *State Hope Scale*

The State Hope Scale [58] is a 6-item self-report scale designed to evaluate hope in youth, including two reliable subscales: agency and pathways. The “agency” subscale measures perceived ability to generate plans and work towards one’s goals (eg, “I can think of many ways to reach my current goals”); the “pathways” subscale reflects perceived success in meeting those goals (eg, “At this time, I am meeting the goals I have set for myself”). In Project YES, we expected possible shifts in *agency* scores, but not in *pathways* scores, as participants would not have had opportunities to pursue goals in a new way from pre- to immediately post-SSI. Thus, we indexed hope using the 3-item agency subscale of the State Hope Scale. Immediately pre- and post-intervention, participants rated each of 3 statements to reflect how they felt about themselves right now on an 8-point Likert scale (0=“definitely false”; 8=“definitely true”). Internal consistency was α=.74 and α=.82 at pre- and post-SSI, respectively.

### *Beck Hopelessness Scale-4*

The Beck Hopelessness Scale-4 (BHS-4) [59] is a reliable, shortened version of the 20-item scale used to measure hopelessness in youth [60]. Immediately pre- and post-intervention, participants rated each of 4 statements to indicate their sense of hopelessness “right now, in this moment” on a 4-point Likert scale (0=“absolutely disagree”; 3=“absolutely agree”). Internal consistency was α=.85 and α=.89 at pre- and post-SSI, respectively.

### *Self-Hate Scale*

The Self Hate Scale [61] is a reliable, 7-item measure designed to measure feelings of self-hatred. A shortened, 3-item version of the original scale was adapted for this study. Items were formally selected using confirmatory factor analysis in an initial sample of N=246 adolescents from the same age group (ages 11-17; see Multimedia Appendix 1). Immediately pre- and post-intervention, participants rated how true each of 3 statements was for them right now (“I hate myself,” “I feel disgusted when I think about myself,” “I feel ashamed of myself”) on a 6-point Likert scale (1=“not at all true for me”; 6=“very true for me”). Internal consistency was α=.92 and α=.94 at pre- and post-SSI, respectively.

### *Perceived Control*

A single-item measure of adolescent perceived control was developed for this study. Immediately pre- and post-intervention, participants rated agreement with the statement, “right now, I feel like things are out of my control” from 0-10 (“not at all” to “a lot”).

### *Perceived Change in Hopelessness and Problem-Solving*

Two questions, developed for use in the present study based on previously established guidelines for assessing subjectively perceived change following an intervention [62], evaluated participants’ perceived change in hopelessness and ability to solve problems. Immediately post-intervention, these questions asked, “to what extent are you feeling hopeless right now?” and, “to what extent are you able to solve the problems facing you right now?”, when “compared to before doing this activity.” Perceived change in hopelessness and problem-solving ability were both rated on a 5-point Likert scale (“much more hopeless” to “a lot less hopeless”; “much less able to solve problems” to “a lot more able to solve problems”). These measures were created based on established methods used to calculate the “smallest effect size of interest,” or the smallest possible effect size associated with a detectable, subjective change within individuals [62].

### *Program Feedback Scale*

The Program Feedback Scale (PFS) [63], which is routinely used to evaluate acceptability and user perceptions of SSIs [64-67], asks participants to rate agreement with seven statements indicating perceived acceptability and feasibility of their selected SSI (eg, “I enjoyed the program”) on a 5-point Likert scale (1=“really disagree”; 5=“totally agree”). The scale was adapted from existing, validated acceptability assessments of digital interventions; adaptations from existing scales were necessary in order to exclude items that are inapplicable to web-based SSIs (eg, items referencing frequency of use or interest in continuing to revisit the program). The PFS also assessed participants’ open-response feedback. PFS item scores may be evaluated individually or via a mean-score across items. Internal consistency across PFS items was α=.88, but mean responses to *each* PFS items were considered independently in this study to inform understandings of acceptability in specific domains (eg, enjoyability, ease of use, ease of understanding).

## Analytic Plan

### *Sample Characterization and Usage Patterns*

To assess YES usage patterns, we identified numbers of youths who began YES; selected, started, and completed an SSI; which SSI youths selected; and demographics, symptom levels, and hopelessness, self-hate, and for youths who selected, started, and completed an SSI. For youths who completed an SSI and the PFS, we computed overall and item-level means to assess the acceptability and feasibility of each SSI. Per our preregistration, mean scores of >3 on any PFS item indicates item endorsement (ie, positive feedback/adequate acceptability); a mean *overall* score of >3, across all items, reflects overall perceived SSI acceptability. Using the sub-sample of SSI completers, descriptive statistics for pre-to-post SSI “perceived change” items were computed. Mean ratings >0 on either item indicated an overall, subjectively detectable pre-to-post SSI change on that dimension (*hopelessness* or *problem-solving ability*).

### *SSI Effects on Proximal Outcomes*

Within-group effect sizes (Cohen *d*, including 95% confidence intervals) were computed reflecting the change in pre-SSI to post-SSI levels of each immediate post-SSI outcome variable (hopelessness, self-hate, agency), both across and within SSIs. Because there are multiple approaches to computing Cohen *d* for within-subject designs [68], we report both $d_{av}$ (1) and $d_z$ (2) to maximize transparency:

$$\text{Cohen } d_{av}=M_{diff}/((SD_1+SD_2)/2)\ \textbf{(1)}$$

$$\text{Cohen } d_z=M_{diff}/\sqrt{(\Sigma((x_{diff}-M_{diff})^2/(N\text{-}1))}\ \textbf{(2)}$$

When the correlation between pre- and post-intervention outcome assessments is $r>0.5$, $d_z$ is larger than $d_{av}$; when $r<0.5$, Cohen $d_z$ is smaller than Cohen $d_{av}$. Whereas $d_z$ accounts for within-subject correlations between pre- and post-program measures, $d_{av}$ does not. Here, conclusions were drawn based on patterns of effect sizes across both approaches to computing Cohen *d*.

All available data were used for each test described above. Missing data rates are reported but not imputed, as usage patterns (including attrition) were of direct empirical interest. Anonymized data and code for all analyses are available via the Open Science Framework [50].

# Results

## Sample and Usage Patterns in YES

From September 2019 to March 2020, 694 youths accessed Project YES, of whom 612 selected, 539 began, and 187 finished a 30-minute SSI, for an overall completion rate of 34.32% among those who began an intervention (see Tables 1 and 2 for details). Those who selected, began, and completed an SSI reported clinically elevated depressive symptoms, on average (per an SMFQ cut-off score of 11 for early adolescents [69], established via comparisons with diagnostic interviews and validated depression screening measures), and were diverse on several dimensions (across all youths who accessed YES: 53.28% non-white, N=373; 78.98% biologically female, N=542; 50.13% identified as non-heterosexual, N=399; see Table 1 for details). Among those who selected an SSI, 43.30% (N=265) chose Project Personality (30.67% completion rate among those who began the SSI, N=74), 19.45% (N=119) chose Project CARE (37.37% completion rate among those who began the SSI, N=38), and 37.25% (N=228) chose the ABC Project (37.13% completion rate among those who began the SSI, N=75). Completion rates did not differ significantly from one another. Among youths who began an SSI, users ages 11-13 completed their chosen programs at higher rates than older users (57.75% of 11-13 year-olds, N=41; 29.45% of 14-16 year-olds, N=97; and 33.09% of 17 to <18 year-olds, N=46). Biological sex (male versus female versus intersex), sexual orientation (non-heterosexual versus heterosexual), racial/ethnic identity, and depressive symptom severity (total SMFQ score) were not associated with odds of SSI completion.

**Table 1.** Full sample demographics by SSI completion status.

| Demographic characteristic | Total Sample, mean (SD) or N (%) | Selected an SSI, mean (SD) or N (%) | Started an SSI, mean (SD) or N (%) | Completed an SSI, mean (SD) or N (%) |
|---|---|---|---|---|
| N | 694 | 612 | 539 | 187 |
| SMFQ[a] | 17.09 (6.41) | 17.09 (6.41) | 17.09 (6.43) | 16.51 (6.34) |
| **Age** | | | | |
| <10 | 6 (0.86%) | 5 (0.82%) | 3 (0.56%) | 3 (1.60%) |
| 11 to <13 | 93 (13.40%) | 80 (13.07%) | 71 (13.17%) | 41 (21.93%) |
| 14 to <16 | 416 (59.94%) | 367 (59.97%) | 326 (60.48%) | 97 (51.87%) |
| 17 to <18 | 178 (25.65%) | 159 (25.98%) | 139 (25.79%) | 46 (24.60%) |
| Missing | 1 (0.14%) | 1 (0.16%) | 0 (0%) | 0 (0%) |
| **Race/ethnicity** | | | | |
| White | 321 (46.25%) | 295 (48.20%) | 259 (48.05%) | 89 (47.59%) |
| Black | 19 (2.74%) | 14 (2.29%) | 11 (2.04%) | 5 (2.67%) |
| Latino/Hispanic | 18 (2.59%) | 15 (2.45%) | 11 (2.04%) | 3 (1.60%) |
| Asian | 89 (12.82%) | 72 (11.77%) | 65 (12.06%) | 17 (9.09%) |
| Multiracial | 46 (6.63%) | 43 (7.03%) | 41 (7.61%) | 19 (10.16%) |
| Other | 194 (27.95%) | 168 (27.45%) | 149 (27.64%) | 54 (28.88%) |
| Missing | 7 (1.01%) | 5 (0.82%) | 3 (0.56%) | 0 (0%) |
| **Sex** | | | | |
| Female | 542 (78.10%) | 478 (78.11%) | 429 (79.59%) | 150 (80.21%) |
| Male | 142 (20.46%) | 125 (20.43%) | 105 (19.48%) | 36 (19.25%) |
| Intersex | 2 (0.29%) | 1 (0.16%) | 1 (0.19%) | 0 (0%) |
| Missing | 9 (1.30%) | 8 (1.31%) | 4 (0.74%) | 1 (0.53%) |
| **Gender identity differs from sex** | | | | |
| Yes | 147 (21.18%) | 124 (20.26%) | 113 (20.97%) | 45 (24.06%) |
| No | 489 (70.46%) | 438 (71.57%) | 385 (71.43%) | 130 (69.52%) |
| Unsure | 48 (6.91%) | 42 (6.86%) | 37 (6.87%) | 11 (5.89%) |
| Missing | 10 (1.44%) | 8 (1.31%) | 4 (0.74%) | 1 (0.53%) |
| **Sexual orientation** | | | | |
| Heterosexual | 295 (42.51%) | 269 (43.95%) | 235 (43.60%) | 83 (44.39%) |
| Homosexual | 6 (0.86%) | 6 (0.98%) | 5 (0.93%) | 0 (0%) |
| Bisexual | 104 (14.99%) | 97 (15.85%) | 85 (15.77%) | 28 (14.97%) |
| Queer | 12 (1.73%) | 12 (1.96%) | 10 (1.86%) | 4 (2.14%) |
| Gay | 12 (1.73%) | 12 (1.96%) | 10 (1.86%) | 2 (1.07%) |
| Lesbian | 29 (4.18%) | 26 (4.25%) | 25 (4.64%) | 8 (4.28%) |
| Pansexual | 32 (4.61%) | 29 (4.74%) | 28 (5.20%) | 10 (5.35%) |
| Asexual | 19 (2.74%) | 17 (2.78%) | 15 (2.78%) | 7 (3.74%) |
| Other | 31 (4.47%) | 28 (4.58%) | 24 (4.45%) | 7 (3.74%) |
| Unsure | 55 (7.93%) | 50 (8.17%) | 47 (8.72%) | 18 (9.63%) |
| No response | 50 (7.20%) | 44 (7.19%) | 38 (7.05%) | 16 (8.56%) |
| Missing | 49 (7.06%) | 22 (3.60%) | 17 (3.15%) | 4 (2.14%) |

[a] SMFQ: Mood and Feelings Questionnaire—Short.

**Table 2.** Demographics and mean depressive symptoms among SSI completers, by selected SSI

| Demographic characteristic | ABC Project, mean (SD) or N (%) | Project CARE, mean (SD) or N (%) | Project Personality, mean (SD) or N (%) |
|---|---|---|---|
| N | 75 | 38 | 74 |
| SMFQ[a] | 17.47 (6.84) | 16.24 (6.80) | 15.69 (5.46) |
| **Age** | | | |
| <10 | 1 (1.33%) | 2 (5.26%) | 0 |
| 11 to 13 | 16 (21.33%) | 9 (23.68%) | 16 (21.62%) |
| 14 to 16 | 47 (62.67%) | 18 (47.37%) | 32 (43.24%) |
| 17 to <18 | 11 (14.67%) | 9 (23.68%) | 26 (35.14%) |
| **Race/ethnicity** | | | |
| White | 33 (44.00%) | 18 (47.37%) | 38 (51.35%) |
| Black | 3 (4.00%) | 1 (2.63%) | 1 (1.35%) |
| Latino/Hispanic | 1 (1.33%) | 0 (0%) | 2 (2.70%) |
| Asian | 4 (5.33%) | 4 (10.53%) | 9 (12.16%) |
| Other | 26 (34.67%) | 10 (26.32%) | 18 (24.32%) |
| Multiple | 8 (10.66%) | 5 (13.15%) | 6 (8.11%) |
| **Sex** | | | |
| Female | 63 (85.14%) | 28 (73.68%) | 59 (79.73%) |
| Male | 11 (14.86%) | 10 (26.32%) | 15 (20.27%) |
| Intersex | 0 (0%) | 0 (0%) | 0 (0%) |
| **Gender identity differs from sex** | | | |
| Yes | 20 (27.03%) | 11 (28.95%) | 14 (18.92%) |
| No | 49 (66.22%) | 25 (65.79%) | 56 (75.68%) |
| Unsure | 5 (6.76%) | 2 (5.26%) | 4 (5.41%) |
| **Sexual orientation** | | | |
| Heterosexual | 27 (36.99%) | 23 (62.16%) | 33 (45.21%) |
| Homosexual | 0 (0%) | 0 (0%) | 0 (0%) |
| Bisexual | 10 (13.70%) | 4 (10.81%) | 14 (19.18%) |
| Queer | 0 (0%) | 3 (8.11%) | 1 (1.37%) |
| Gay | 1 (1.37%) | 0 (0%) | 1 (1.37%) |
| Lesbian | 6 (8.22%) | 1 (2.70%) | 1 (1.37%) |
| Pansexual | 7 (9.59%) | 2 (5.41%) | 1 (1.37%) |
| Asexual | 3 (4.11%) | 1 (2.70%) | 3 (4.11%) |
| Other | 4 (5.48%) | 0 (0%) | 3 (4.11%) |
| Unsure | 8 (10.96%) | 1 (2.70%) | 9 (12.33%) |
| No response | 7 (9.59%) | 2 (5.41%) | 7 (9.59%) |

[a] SMFQ: Mood and Feelings Questionnaire—Short.

On average, youths who completed YES in full spent 44.71 minutes on the YES website (SD 37.24 minutes; median 34.96 minutes; range 10.95-292.23 minutes), inclusive of all questionnaires, their chosen SSI, and writing anonymous coping advice for the YES Advice Center. Across all youths who accessed the website, including those who neither began nor completed an SSI, average time spent on YES was 27.92 minutes; this value did not differ significantly across the three programs.

### *Did Youths Perceive YES as Acceptable?*

Youths who completed an SSI and the PFS (N=187), both collapsing across SSIs and within each SSI (Table 3; all item-level means >3.50/5), found YES acceptable. Overall, youths rated their chosen SSI as enjoyable (3.72/5.00), easy to understand (4.25/5.00), easy to use (4.31/5.00), likely to help their peers (4.04/5.00), and worth recommending to others (3.83/4.00). Youths also generally endorsed trying their hardest on the SSI (3.83/5.00) and agreement with the SSI's message (4.29/5.00). Ratings on these items did not differ by SSI selection.

**Table 3.** Means and standard deviations of Program Feedback Scale items among SSI completers, by selected SSI and across all SSIs, mean (SD).

| Item | ABC Project | Project CARE | Project Personality | All SSIs |
|---|---|---|---|---|
| Enjoy | 3.57 (1.03) | 3.84 (0.75) | 3.81 (1.00) | 3.72 (0.97) |
| Understood | 4.16 (0.85) | 4.08 (0.88) | 4.43 (0.74) | 4.25 (0.83) |
| Easy to use | 4.28 (0.83) | 4.21 (0.74) | 4.39 (0.76) | 4.31 (0.78) |
| Tried hardest | 3.85 (1.09) | 3.55 (1.08) | 3.95 (1.03) | 3.83 (1.07) |
| Helpful | 3.97 (1.08) | 4.16 (0.89) | 4.05 (1.06) | 4.04 (1.03) |
| Recommend to friend | 3.72 (1.16) | 3.95 (1.01) | 3.89 (1.15) | 3.83 (1.13) |
| Agree with message | 4.11 (0.95) | 4.47 (0.76) | 4.38 (0.75) | 4.29 (0.85) |
| Full scale | 3.95 (0.82) | 4.04 (0.61) | 4.13 (0.69) | 4.04 (0.73) |

### *Did Hopelessness, Agency, Perceived Control, and Self-Hatred Improve From Before to After YES?*

We tested SSI short-term utility both across SSIs, given their common structures and shared principles underlying each program's development, and separately, as each SSI differed in content. Across SSIs, and for each SSI separately, effect sizes $d_{av}$ and $d_z$, 95% confidence intervals are reported (Table 4). Collapsing across SSIs, youths reported significant pre-to-post-SSI improvements in all proximal outcomes, regardless of the *d* computation approach. For overall reductions in self-hatred, small-to-medium effects emerged ($d_{av}$=0.32, 95% CI 0.16, 0.47; $d_z$=0.61, 95% CI 0.44, 0.77), with post-SSI self-hatred showing a 55% chance of being lower than pre-SSI self-hatred (per the “common language effect size” estimate; see [68]). For overall reductions in hopelessness, medium-to-large effects emerged ($d_{av}$=0.53, 95% CI 0.37, 0.69; $d_z$=0.71, 95% CI 0.54, 0.87), with post-SSI hopelessness showing a 62% chance of being lower than pre-SSI hopelessness. For overall improvements in agency, small-to-medium effects emerged ($d_{av}$=0.39, 95% CI 0.24, 0.55; $d_z$=0.50, 95% CI 0.34, 0.65), with post-SSI agency showing a 59% chance of being higher than the pre-SSI agency. For overall improvements in perceived control, medium-to-large effects emerged ($d_{av}$=0.60, 95% CI 0.44, 0.76; $d_z$=0.72, 95% CI 0.55, 0.89), with post-SSI self-hatred scores showing a 64% chance of being lower than pre-SSI scores. SSI-specific effect sizes fell within similar ranges (see Table 3). Within and across SSIs, 95% effect size confidence intervals overlapped across proximal outcomes, suggesting no detectable differences in youths' pre-to-post-program changes in hopelessness, self-hatred, agency, or perceived control as a function of SSI selection.

**Table 4.** Means, standard deviations, and effect sizes by selected SSI; mean (SD) or (95% CI).

| Outcome variable | ABC Project | Project CARE | Project Personality |
|---|---|---|---|
| **Agency** | | | |
| Pre-SSI | 4.36 (1.69) | 4.66 (1.62) | 4.69 (1.64) |
| Post-SSI | 5.03 (1.84) | 5.42 (1.34) | 5.24 (1.73) |
| $d_{av}$ (95% CI) | 0.40 (0.15, 0.65) | 0.58 (0.20, 0.95) | 0.31 (0.07, 0.55) |
| $d_z$ (95% CI) | 0.60 (0.34, 0.86) | 0.65 (0.26, 1.02) | 0.34 (0.10, 0.58) |
| **Hopelessness** | | | |
| Pre-SSI | 2.81 (0.82) | 2.75 (0.79) | 2.59 (0.86) |
| Post-SSI | 2.38 (0.89) | 2.16 (0.80) | 2.13 (0.76) |
| $d_{av}$ | 0.44 (0.19, 0.69) | 0.83 (0.44, 1.21) | 0.49 (0.25, 0.74) |
| $d_z$ | 0.62 (0.36, 0.87) | 1.01 (0.60, 1.42) | 0.66 (0.40, 0.91) |
| **Self-hate** | | | |
| Pre-SSI | 4.15 (1.74) | 4.05 (1.70) | 3.79 (1.74) |
| Post-SSI | 3.57 (1.65) | 3.49 (1.80) | 3.13 (1.80) |
| $d_{av}$ | 0.31 (0.06, 0.55) | 0.35 (–0.02, 0.71) | 0.31 (0.07, 0.55) |
| $d_z$ | 0.65 (0.38, 0.91) | 0.72 (0.32, 1.11) | 0.54 (0.29, 0.79) |
| **Perceived control** | | | |
| Pre-SSI | 6.72 (2.81) | 6.43 (2.65) | 6.32 (2.77) |
| Post-SSI | 5.12 (2.76) | 4.69 (2.66) | 4.90 (2.19) |
| $d_{av}$ | 0.54 (0.29, 0.79) | 0.75 (0.35, 1.14) | 0.59 (0.33, 0.85) |
| $d_z$ | 0.68 (0.41, 0.94) | 1.03 (0.59, 1.45) | 0.65 (0.38, 0.90) |

### *Did Youths Subjectively Detect Changes in Hopelessness and Problem-Solving Ability From Before to After YES?*

Collapsing across SSIs, at post-intervention, 15.6% (N=29) of youths reported feeling “much less hopeless” compared to before beginning the SSI; 53.1% (N=99) felt “a little less hopeless”; 27.9% (N=52) felt “the same amount hopeless”; 3.4% (N=6) felt “a little more hopeless”; and 0.0% (N=0) felt “a lot more hopeless.” Separately, 8.4% (N=16) of youths reported feeling “much more able to solve problems” compared to before beginning the SSI; 50.0% (N=93) felt “a little more able to solve problems”; 38.8% (N=72) felt “the same amount able to solve problems”; 2.8% (N=5) felt “a little less able to solve problems”; and 0.0% (N=0) felt “a lot less able to solve problems.”

## Discussion

This nonexperimental study evaluated the perceived acceptability and short-term effects of Project YES, an open-access platform for youths offering three 30-minute, self-directed SSIs, each teaching a strategy for coping with internalizing distress. Regardless of SSI selection, youths who completed an SSI reported significant pre-to-post-program reductions in hopelessness ($d_{av}$=0.53; $d_z$=0.71), self-hate ($d_{av}$=0.32; $d_z$=0.61), perceived control ($d_{av}$=0.60; $d_z$=0.72) and agency ($d_{av}$=0.39; $d_z$=0.50). Youths who completed an SSI rated it as enjoyable, easy to understand, likely to help peers, and worth recommending to others, and there was no evidence for adverse SSI effects (eg, no youths reported feeling “much more hopeless” or “much less able to solve problems” after program completion). Based on largely overlapping confidence intervals for $d_{av}$ and $d_z$, no evidence emerged for differential SSI effects on proximal outcomes.

Findings reinforce and extend evidence supporting the utility of SSIs for youth experiencing internalizing distress [19,20,53]. Past studies have raised the possibility that open-access, online SSIs might benefit youths experiencing elevated symptoms. However, no studies have tested their acceptability or utility in naturalistic settings (versus in controlled trials, which offer participation incentives, necessitate parental involvement, and prevent youth from choosing which SSIs they wish to receive). This study provides the first evidence that online SSIs may be acceptable—and potentially helpful—when delivered in the “real-world” as free, publicly available supports. Within-group post-SSI effects were modest; even so, the accessibility, cost-free nature, and brevity of YES suggest its public health value, particularly if available continuously and on a large scale. The self-selected youth sample reported elevated depressive symptoms (among all youths who started YES, SMFQ mean 17.06, SD 6.40, and among youths who completed a YES SSI, SMFQ mean 16.51, SD 6.34, both >50% higher than commonly used screening cut-offs for adolescent depression [69]), indicating the acceptability and possible utility of YES among youths with immediate clinical needs.

In addition to frequently reporting clinically elevated depressive symptoms, many youths accessing YES reported one or more marginalized identities, including sexual minority status (50.13% of users) and racial/ethnic minority status (53.28% of users). YES includes no exclusion or screening criteria—youths from these communities *self-selected* into participation—and no formal efforts were made to recruit members of specific groups. Thus, YES and similar platforms may represent efficient avenues for providing support to youths that may be likely to need, but unlikely to access traditional services. Simultaneously, more female than male adolescents self-selected into YES. This discrepancy may reflect higher rates of depression among adolescent girls versus boys, but it also fits with research suggesting that boys who are experiencing depression access treatment less often than girls [70]. Future work may focus on redesigning YES-like platforms that appeal to adolescents regardless of sex.

Regarding usability, more than 34% of youths who began an SSI finished it. This rate compares favorably with prior studies of “real-world” engagement with self-directed, tech-based psychological supports (1-28% retention) [15,70], and even with rates of retention in outpatient youth psychotherapy (premature drop-out rates range from 16-75%) [71,72]. However, Project YES is the first naturalistic evaluation of web-based, youth-directed SSIs; thus, further research is needed to gauge whether a 34% completion rate is typical of this type of program, as well as the degree to which this rate could be improved. Systematically testing strategies for further improving retention in YES-like platforms will be valuable—especially among older users (above age 14), for whom completion rates were lower than for younger users (ages 13 and younger). Retention may be improved by eliminating or minimizing questionnaires (all YES questionnaires are optional, but their presence may be a deterrence) and decreasing intervention length and iteratively re-testing ‘hyper-brief’ SSIs for acceptability and utility. Other revisions may include personalizing intervention content for youths of different age ranges or developmental stages and optimizing YES for smartphone-based completion (currently, YES is completable across internet-equipped devices but is optimized for desktop and laptop users).

No evidence emerged for differential SSI effects on hopelessness, perceived control, agency, or self-hatred, although each SSI was initially intended to target a different proximal outcome. Project CARE was designed to reduce self-hatred, Project Personality was designed to strengthen perceived control and combat hopelessness, and the ABC Project was intended to strengthen perceived agency over behavior. However, no evidence emerged for domain-specific effects across SSIs. This outcome, while quite preliminary, fits with existing evidence that change-mechanisms may be more similar than different across psychotherapies [19,73]. Here, each SSI was designed according to a common set of principles [19] and included several elements in common (eg, neuroscience-based psychoeducation; testimonials from scientists and peers; opportunities to offer advice to others), which themselves may promote a shared set of adaptive thinking styles.

A second possibility is that the constructs assessed in this study—and clinical psychology intervention research more broadly—have shown considerable overlap, both conceptually and statistically [74,75], and may not reflect entirely distinct constructs. Additional measurement-focused work is needed to determine the extent to which self-report assessments of agency, perceived control, hopelessness, self-hate, and numerous other “thinking styles” commonly studied in intervention research reflect genuinely distinct factors, versus features of a shared latent construct.

A third possibility involves the role of *personal choice* on the platform. YES users independently decide not only whether to participate, but which SSI to complete and whether to publicly share anonymous advice with peers. These opportunities to exert agency, common across YES SSIs, may contribute to similar cross-program outcomes, at least proximally. This possibility is especially relevant to adolescents, for whom autonomy and assertion are both highly motivating and key developmental tasks. Future work may formally test how personal choice and opportunities to develop autonomy shape adolescents’ receptivity and response to YES-like support—and to mental health treatment more broadly.

Study limitations suggest directions for future research. First, this study is nonexperimental, observational, and anonymous. All of these features are necessary given the study’s objectives (to evaluate acceptability and utility of SSIs in naturalistic settings), but results should be interpreted with caution. For instance, despite targeted social media-based advertising, it is impossible to determine with certainty that participants were sincere when reporting their age-ranges. Further, as in any non-randomized program evaluation, possible selection bias cannot be overlooked. For instance, youths who self-initiate and complete a given SSI may be those most likely to benefit from it; thus, present findings may not reflect the SSIs’ utility for *all* youths. Future randomized trials that proactively address selection bias are needed to unpack this possibility. Third, given the anonymous nature of YES, we could not follow-up with participants; however, prior trials suggest these and similar SSIs confer longer-term clinical benefits [19,42,53]. Additionally, our SSIs are available only in English at this time, limiting access for large portions of the global population. Translation and further pilot-testing are needed to begin gauging the cross-contextual, cross-cultural promise of YES and similar platforms.

Overall, results suggest that open-access, free of charge SSIs for adolescents ages 11-17 are acceptable; associated with proximal improvements in hopelessness, agency, perceived control, and self-hatred; and show no evidence for adverse effects. Overall, YES users were more likely to perceive *some* psychological benefits than *none*—either in hopelessness, problem-solving skills, or both. Certainly, YES-like platforms cannot and should not replace longer-term psychotherapies—but they may offer much-needed low-cost, easily accessible support to the many youths who might otherwise go without treatment. Future work may examine the broader-scale use of YES across cultures, integration of YES-like platforms with more intensive forms of support, and systematically examine the role of SSI choice in adolescents’ response to similar interventions.

## Conflicts of Interest

JLS receives grant and research support from the National Institutes of Health (DP5OD28123), the Klingenstein Third Generation Foundation, the American Psychological Foundation, and Limbix, Inc. MD receives grant support from a Stony Brook University Graduate Research Fellowship. MD, JS, and EM receive research funding from the Psi Chi Honor Society. JLS, MD, and MCM are under contract with New Harbinger Publications to co-author a therapeutic workbook for adolescents. JLS is under contract with Oxford University Press to co-edit a book on low-intensity mental health interventions for youth. The authors report no other financial conflicts.

Multimedia Appendix 1
Project YES Analytic Code and Supplementary Analyses.
[DOCX File , 98 KB - mental_v7i6e20513_app1.docx ]

## References

1. Kazdin AE, Rabbitt SM. Novel Models for Delivering Mental Health Services and Reducing the Burdens of Mental Illness. Clinical Psychological Science 2013 Jan 23;1(2):170-191. [doi: 10.1177/2167702612463566]
2. Konrad TR, Ellis AR, Thomas KC, Holzer CE, Morrissey JP. County-Level Estimates of Need for Mental Health Professionals in the United States. PS 2009 Oct;60(10):1307-1314 [FREE Full text] [doi: 10.1176/ps.2009.60.10.1307]
3. Powell AC, Torous JB, Firth J, Kaufman KR. Generating value with mental health apps. BJPsych Open 2020 Feb 05;6(2):e16 [FREE Full text] [doi: 10.1192/bjo.2019.98] [Medline: 32019619]
4. Torous J, Wisniewski H, Liu G, Keshavan M. Mental Health Mobile Phone App Usage, Concerns, and Benefits Among Psychiatric Outpatients: Comparative Survey Study. JMIR Ment Health 2018 Nov 16;5(4):e11715. [doi: 10.2196/11715]
5. Pew RC. Teens, Social Media & Technology 2018 Internet. Pew Research Center. URL: https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/ [accessed 2020-02-28]
6. Firth J, Torous J, Nicholas J, Carney R, Pratap A, Rosenbaum S, et al. The efficacy of smartphone-based mental health interventions for depressive symptoms: a meta-analysis of randomized controlled trials. World Psychiatry 2017 Oct;16(3):287-298 [FREE Full text] [doi: 10.1002/wps.20472] [Medline: 28941113]
7. Kerst A, Zielasek J, Gaebel W. Smartphone applications for depression: a systematic literature review and a survey of health care professionals' attitudes towards their use in clinical practice. Eur Arch Psychiatry Clin Neurosci 2020 Mar;270(2):139-152. [doi: 10.1007/s00406-018-0974-3] [Medline: 30607530]
8. Christie GI, Shepherd M, Merry SN, Hopkins S, Knightly S, Stasiak K. Gamifying CBT to deliver emotional health treatment to young people on smartphones. Internet Interv 2019 Dec;18:100286 [FREE Full text] [doi: 10.1016/j.invent.2019.100286] [Medline: 31890633]
9. Bevan Jones R, Thapar A, Rice F, Mars B, Agha SS, Smith D, et al. A Digital Intervention for Adolescent Depression (MoodHwb): Mixed-Methods Feasibility Evaluation. JMIR Ment Health 2020 Feb 02 [FREE Full text] [doi: 10.2196/14536] [Medline: 32384053]
10. Cliffe B, Croker A, Denne M, Smith J, Stallard P. Digital Cognitive Behavioral Therapy for Insomnia for Adolescents With Mental Health Problems: Feasibility Open Trial. JMIR Ment Health 2020 Mar 03;7(3):e14842 [FREE Full text] [doi: 10.2196/14842] [Medline: 32134720]
11. Fleming TM, de Beurs D, Khazaal Y, Gaggioli A, Riva G, Botella C, et al. Maximizing the Impact of e-Therapy and Serious Gaming: Time for a Paradigm Shift. Front Psychiatry 2016;7:65 [FREE Full text] [doi: 10.3389/fpsyt.2016.00065] [Medline: 27148094]
12. Fleming TM, Bavin L, Stasiak K, Hermansson-Webb E, Merry SN, Cheek C, et al. Serious Games and Gamification for Mental Health: Current Status and Promising Directions. Front Psychiatry 2016;7:215 [FREE Full text] [doi: 10.3389/fpsyt.2016.00215] [Medline: 28119636]
13. Wasil AR, Venturo-Conerly KE, Shingleton RM, Weisz JR. A review of popular smartphone apps for depression and anxiety: Assessing the inclusion of evidence-based content. Behav Res Ther 2019 Dec;123:103498. [doi: 10.1016/j.brat.2019.103498] [Medline: 31707224]
14. Punukollu M, Marques M. Use of mobile apps and technologies in child and adolescent mental health: a systematic review. Evid Based Ment Health 2019 Nov;22(4):161-166. [doi: 10.1136/ebmental-2019-300093] [Medline: 31358537]
15. Fleming T, Bavin L, Lucassen M, Stasiak K, Hopkins S, Merry S. Beyond the Trial: Systematic Review of Real-World Uptake and Engagement With Digital Self-Help Interventions for Depression, Low Mood, or Anxiety. J Med Internet Res 2018 Jun 06;20(6):e199 [FREE Full text] [doi: 10.2196/jmir.9275] [Medline: 29875089]
16. Liverpool S, Mota CP, Sales CMD, Čuš A, Carletto S, Hancheva C, et al. Engaging Children and Young People in Digital Mental Health Interventions: Systematic Review of Modes of Delivery, Facilitators, and Barriers. J Med Internet Res 2020 Mar 12 [FREE Full text] [doi: 10.2196/16317] [Medline: 32442160]

17. Schleider JL, Weisz JR. Little Treatments, Promising Effects? Meta-Analysis of Single-Session Interventions for Youth Psychiatric Problems. J Am Acad Child Adolesc Psychiatry 2017 Feb;56(2):107-115. [doi: 10.1016/j.jaac.2016.11.007] [Medline: 28117056]
18. Weisz JR, Kuppens S, Ng MY, Eckshtain D, Ugueto AM, Vaughn-Coaxum R, et al. What five decades of research tells us about the effects of youth psychological therapy: A multilevel meta-analysis and implications for science and practice. Am Psychol 2017;72(2):79-117. [doi: 10.1037/a0040360] [Medline: 28221063]
19. Schleider JL, Dobias ML, Sung JY, Mullarkey MC. Future Directions in Single-Session Youth Mental Health Interventions. J Clin Child Adolesc Psychol 2020;49(2):264-278. [doi: 10.1080/15374416.2019.1683852] [Medline: 31799863]
20. Schleider J, Weisz J. A single-session growth mindset intervention for adolescent anxiety and depression: 9-month outcomes of a randomized trial. J Child Psychol Psychiatry 2018 Feb;59(2):160-170. [doi: 10.1111/jcpp.12811] [Medline: 28921523]
21. Schleider JL, Burnette JL, Widman L, Hoyt C, Prinstein MJ. Randomized Trial of a Single-Session Growth Mind-Set Intervention for Rural Adolescents' Internalizing and Externalizing Problems. J Clin Child Adolesc Psychol 2019 Jun 20:1-13. [doi: 10.1080/15374416.2019.1622123] [Medline: 31219698]
22. Miu AS, Yeager DS. Preventing Symptoms of Depression by Teaching Adolescents That People Can Change. Clinical Psychological Science 2014 Sep 15;3(5):726-743. [doi: 10.1177/2167702614548317]
23. Project YES: Youth Empowerment & Support. Lab for Scalable Mental Health. Stony Brook: Stony Brook University URL: http://www.schleiderlab.org/YES.html [accessed 2020-06-19]
24. Pössel P, Smith E. Integrating Beck's Cognitive Theory of Depression and the Hopelessness Model in an Adolescent Sample. J Abnorm Child Psychol 2020 Mar;48(3):435-451. [doi: 10.1007/s10802-019-00604-8] [Medline: 31832835]
25. Gibb BE, Alloy LB. A prospective test of the hopelessness theory of depression in children. J Clin Child Adolesc Psychol 2006 Jun 07;35(2):264-274 [FREE Full text] [doi: 10.1207/s15374424jccp3502_10] [Medline: 16597222]
26. Rubenstein LM, Alloy LB, Abramson LY. Perceived Control and Depression: Forty Years of Research. In: Reich JW, Infurna FJ, editors. Perceived Control: Theory, Research, and Practice in the First 50 Years. Oxford: Oxford Scholarship Online; 2016:246.
27. Moè A. Perceived Control Mediates the Relations between Depressive Symptoms and Academic Achievement in Adolescence. Span J Psychol 2015 Sep 17;18:E70. [doi: 10.1017/sjp.2015.68] [Medline: 26377348]
28. Jose PE, Weir KF. Adolescent sense of control: a downward extension of the Shapiro Control Inventory to pre- and early adolescents. J Genet Psychol 2013;174(5-6):494-513. [doi: 10.1080/00221325.2012.713044] [Medline: 24303570]
29. Schleider JL, Abel MR, Weisz JR. Do Immediate Gains Predict Long-Term Symptom Change? Findings from a Randomized Trial of a Single-Session Intervention for Youth Anxiety and Depression. Child Psychiatry Hum Dev 2019 Apr 16;50(5):868-881 [FREE Full text] [doi: 10.1007/s10578-019-00889-2]
30. Dobias ML, Mullarkey MC, Schleider JL. The Teenage Goals Project. Open Science Framework. 2019. URL: https://osf.io/57b3k/ [accessed 2020-02-28]
31. Turnell AI, Fassnacht DB, Batterham PJ, Calear AL, Kyrios M. The Self-Hate Scale: Development and validation of a brief measure and its relationship to suicidal ideation. J Affect Disord 2019 Feb 15;245:779-787. [doi: 10.1016/j.jad.2018.11.047] [Medline: 30448763]
32. Fox KR, Ribeiro JD, Kleiman EM, Hooley JM, Nock MK, Franklin JC. Affect toward the self and self-injury stimuli as potential risk factors for nonsuicidal self-injury. Psychiatry Res 2018 Feb;260:279-285. [doi: 10.1016/j.psychres.2017.11.083] [Medline: 29223043]
33. Pfeiffer PN, Brandfon S, Garcia E, Duffy S, Ganoczy D, Myra Kim H, et al. Predictors of suicidal ideation among depressed Veterans and the interpersonal theory of suicide. J Affect Disord 2014 Jan;152-154:277-281. [doi: 10.1016/j.jad.2013.09.025] [Medline: 24135507]
34. Zelkowitz RL, Cole DA. Self-Criticism as a Transdiagnostic Process in Nonsuicidal Self-Injury and Disordered Eating: Systematic Review and Meta-Analysis. Suicide Life Threat Behav 2019 Feb;49(1):310-327 [FREE Full text] [doi: 10.1111/sltb.12436] [Medline: 29504147]
35. Smith DM, Wang SB, Carter ML, Fox KR, Hooley JM. Longitudinal predictors of self-injurious thoughts and behaviors in sexual and gender minority adolescents. J Abnorm Psychol 2020 Jan;129(1):114-121. [doi: 10.1037/abn0000483] [Medline: 31657599]
36. Halamová J, Kanovský M, Jurková V, Kupeli N. Effect of a Short-Term Online Version of a Mindfulness-Based Intervention on Self-criticism and Self-compassion in a Nonclinical Sample. SP 2018 Dec;60(4):259-273 [FREE Full text] [doi: 10.21909/sp.2018.04.766]
37. Luoma JB, Platt MG. Shame, self-criticism, self-stigma, and compassion in Acceptance and Commitment Therapy. Current Opinion in Psychology 2015 Apr;2:97-101 [FREE Full text] [doi: 10.1016/j.copsyc.2014.12.016]
38. Hooley JM, Fox KR, Wang SB, Kwashie AND. Novel online daily diary interventions for nonsuicidal self-injury: a randomized controlled trial. BMC Psychiatry 2018 Aug 22;18(1):264 [FREE Full text] [doi: 10.1186/s12888-018-1840-6] [Medline: 30134866]
39. Duarte C, Gilbert P, Stalker C, Catarino F, Basran J, Scott S, et al. Effect of adding a compassion-focused intervention on emotion, eating and weight outcomes in a commercial weight management programme. J Health Psychol 2019 Dec 05:1359105319890019. [doi: 10.1177/1359105319890019] [Medline: 31804147]

40. Schleider J, Mullarkey M, Mumper E, Sung J. The ABC Project. Open Science Framework. 2019. URL: https://osf.io/ch2tg/ [accessed 2020-02-28]
41. Snyder C, Sympson S, Ybasco F, Borders T, Babyak M, Higgins R. State Hope Scale. PsycTESTS Dataset 2011. [doi: 10.1037/t01180-000]
42. Gawrysiak M, Nicholas C, Hopko DR. Behavioral activation for moderately depressed university students: Randomized controlled trial. Journal of Counseling Psychology 2009 Jul;56(3):468-475 [FREE Full text] [doi: 10.1037/a0016383]
43. Ritschel LA, Ramirez CL, Jones M, Craighead WE. Behavioral Activation for Depressed Teens: A Pilot Study. Cognitive and Behavioral Practice 2011 May;18(2):281-299 [FREE Full text] [doi: 10.1016/j.cbpra.2010.07.002]
44. Pass L, Lejuez CW, Reynolds S. Brief Behavioural Activation (Brief BA) for Adolescent Depression: A Pilot Study. Behav Cogn Psychother 2018 Mar;46(2):182-194. [doi: 10.1017/S1352465817000443] [Medline: 28756787]
45. Chu BC, Colognori D, Weissman AS, Bannon K. An Initial Description and Pilot of Group Behavioral Activation Therapy for Anxious and Depressed Youth. Cognitive and Behavioral Practice 2009 Nov;16(4):408-419 [FREE Full text] [doi: 10.1016/j.cbpra.2009.04.003]
46. Duckworth AL. Using Psychological Science to Help Children Thrive. Perspect Psychol Sci 2019 Jan;14(1):34-36 [FREE Full text] [doi: 10.1177/1745691618804194] [Medline: 30799740]
47. Eskreis-Winkler L, Milkman KL, Gromet DM, Duckworth AL. A large-scale field experiment shows giving advice improves academic outcomes for the advisor. Proc Natl Acad Sci U S A 2019 Jul 23;116(30):14808-14810 [FREE Full text] [doi: 10.1073/pnas.1908779116] [Medline: 31285348]
48. Eskreis-Winkler L, Fishbach A, Duckworth AL. Dear Abby: Should I Give Advice or Receive It? Psychol Sci 2018 Nov 03;29(11):1797-1806 [FREE Full text] [doi: 10.1177/0956797618795472] [Medline: 30281402]
49. Resnick B. These scientists want to make psychotherapy sessions much, much shorter Internet. Vox. 2019. URL: https://www.vox.com/science-and-health/2019/9/17/20827011/teen-depression-anxiety-treatment-single-session [accessed 2019-09-17]
50. YES (Youth Empowerment & Support). Open Science Framework. URL: https://osf.io/e52p3 [accessed 2020-06-19]
51. Brahmbhatt K, Grupp-Phelan J. Parent-Adolescent Agreement About Adolescent's Suicidal Thoughts: A Divergence. Pediatrics 2019 Feb 14;143(2):e20183071 [FREE Full text] [doi: 10.1542/peds.2018-3071] [Medline: 30642951]
52. Orchard F, Pass L, Cocks L, Chessell C, Reynolds S. Examining parent and child agreement in the diagnosis of adolescent depression. Child Adolesc Ment Health 2019 Sep 28;24(4):338-344 [FREE Full text] [doi: 10.1111/camh.12348]
53. Schleider J, Mullarkey M, Chacko A. Harnessing Wise Interventions to Advance the Potency and Reach of Youth Mental Health Services. Clin Child Fam Psychol Rev 2020 Mar;23(1):70-101. [doi: 10.1007/s10567-019-00301-4] [Medline: 31440858]
54. Aronson E. The power of self-persuasion. American Psychologist 1999 Nov;54(11):875-884 [FREE Full text] [doi: 10.1037/h0088188]
55. Schleider JL, Weisz JR. Project Personality. Open Science Framework. 2019. URL: https://osf.io/a9uv2/ [accessed 2020-02-28]
56. Schleider JL, Weisz JR. Reducing risk for anxiety and depression in adolescents: Effects of a single-session intervention teaching that personality can change. Behav Res Ther 2016 Dec;87:170-181 [FREE Full text] [doi: 10.1016/j.brat.2016.09.011] [Medline: 27697671]
57. Lundervold AJ, Hinshaw SP, Sørensen L, Posserud M. Co-occurring symptoms of attention deficit hyperactivity disorder (ADHD) in a population-based sample of adolescents screened for depression. BMC Psychiatry 2016 Feb 25;16(1):46 [FREE Full text] [doi: 10.1186/s12888-016-0739-3] [Medline: 26915733]
58. Snyder CR, Sympson SC, Ybasco FC, Borders TF, Babyak MA, Higgins RL. Development and validation of the State Hope Scale. J Pers Soc Psychol 1996 Feb;70(2):321-335. [doi: 10.1037//0022-3514.70.2.321] [Medline: 8636885]
59. Perczel Forintos D, Rózsa S, Pilling J, Kopp M. Proposal for a short version of the Beck Hopelessness Scale based on a national representative survey in Hungary. Community Ment Health J 2013 Dec 12;49(6):822-830 [FREE Full text] [doi: 10.1007/s10597-013-9619-1] [Medline: 23756722]
60. Rhoades H, Rusow JA, Bond D, Lanteigne A, Fulginiti A, Goldbach JT. Homelessness, Mental Health and Suicidality Among LGBTQ Youth Accessing Crisis Services. Child Psychiatry Hum Dev 2018 Aug;49(4):643-651. [doi: 10.1007/s10578-018-0780-1] [Medline: 29322361]
61. Turnell AI, Fassnacht DB, Batterham PJ, Calear AL, Kyrios M. The Self-Hate Scale: Development and validation of a brief measure and its relationship to suicidal ideation. J Affect Disord 2019 Feb 15;245:779-787. [doi: 10.1016/j.jad.2018.11.047] [Medline: 30448763]
62. Anvari F, Lakens D. Using Anchor-Based Methods to Determine the Smallest Effect Size of Interest. PsyArXiv Preprints 2019 Jan 31 [FREE Full text] [doi: 10.31234/osf.io/syp5a]
63. Schleider JL, Mullarkey MC, Weisz JR. Virtual Reality and Web-Based Growth Mindset Interventions for Adolescent Depression: Protocol for a Three-Arm Randomized Trial. JMIR Res Protoc 2019 Jul 09;8(7):e13368 [FREE Full text] [doi: 10.2196/13368] [Medline: 31290406]

64. Schleider J, Dobias M, Fassler J, Shroff A, Pati S. Promoting Treatment Access Following Pediatric Primary Care Depression Screening: Randomized Trial of Web-Based, Single-Session Interventions for Parents and Youths. Journal of the American Academy of Child & Adolescent Psychiatry 2020 Jun;59(6):770-773. [doi: 10.1016/j.jaac.2020.01.025]
65. Dobias M, Chen S, Fox K, Schleider J. Brief interventions for self-injurious thoughts and behaviors in young people: A systematic review. Open Science Framework 2020. [doi: 10.31234/osf.io/z26ch]
66. Mullarkey M, Dobias M, Sung J, Shumake J, Beevers C, Schleider J. A scalable, single session intervention for perceived control over anxiety during COVID-19. Open Science Framework 2020. [doi: 10.31234/osf.io/qp7c2]
67. Schleider J, Sung J, Bianco A, Gonzalez A, Vivian D, Mullarkey M. Open Pilot Trial of a Single-Session Consultation Service for Clients on Psychotherapy Wait-Lists. The Behavior Therapist 2020 (forthcoming).
68. Lakens D. Calculating and reporting effect sizes to facilitate cumulative science: a practical primer for t-tests and ANOVAs. Front Psychol 2013 Nov 26;4:863 [FREE Full text] [doi: 10.3389/fpsyg.2013.00863] [Medline: 24324449]
69. Stoep AV, McCauley E, Thompson KA, Herting JR, Kuo ES, Stewart DG, et al. Universal Emotional Health Screening at the Middle School Transition. J Emot Behav Disord 2005 Dec 13;13(4):213-223 [FREE Full text] [doi: 10.1177/10634266050130040301] [Medline: 21430789]
70. Lu W. Adolescent Depression: National Trends, Risk Factors, and Healthcare Disparities. Am J Health Behav 2019 Jan 01;43(1):181-194. [doi: 10.5993/AJHB.43.1.15] [Medline: 30522576]
71. Baruch G, Vrouva I, Fearon P. A Follow-up Study of Characteristics of Young People that Dropout and Continue Psychotherapy: Service Implications for a Clinic in the Community. Child and Adolescent Mental Health 2009:75. [doi: 10.1111/j.1475-3588.2008.00492.x]
72. de Haan AM, Boon AE, de Jong JTVM, Hoeve M, Vermeiren RRJM. A meta-analytic review on treatment dropout in child and adolescent outpatient mental health care. Clin Psychol Rev 2013 Jul;33(5):698-711. [doi: 10.1016/j.cpr.2013.04.005] [Medline: 23742782]
73. Cuijpers P, Reijnders M, Huibers MJH. The Role of Common Factors in Psychotherapy Outcomes. Annu Rev Clin Psychol 2019 May 07;15:207-231. [doi: 10.1146/annurev-clinpsy-050718-095424] [Medline: 30550721]
74. Mullarkey MC, Schleider JL. Contributions of fixed mindsets and hopelessness to anxiety and depressive symptoms: A commonality analysis approach. J Affect Disord 2020 Jan 15;261:245-252. [doi: 10.1016/j.jad.2019.10.023] [Medline: 31669923]
75. Naragon-Gainey K, McMahon TP, Park J. The contributions of affective traits and emotion regulation to internalizing disorders: Current state of the literature and measurement challenges. Am Psychol 2018 Dec;73(9):1175-1186 [FREE Full text] [doi: 10.1037/amp0000371] [Medline: 30525799]

## Abbreviations

**PFS:** Program Feedback Scale
**SMFQ:** Mood and Feelings Questionnaire—Short
**SSI:** single session intervention
**YES:** Youth Empowerment & Support

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Original Paper

# Using Mobile Electroencephalography and Actigraphy to Diagnose Attention-Deficit/Hyperactivity Disorder: Case-Control Comparison Study

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## Abstract

**Background:** Children with attention-deficit/hyperactivity disorder (ADHD), a neurobehavioral disorder, display behaviors of inattention, hyperactivity, or impulsivity, which can affect their ability to learn and establish proper family and social relationships. Various tools are currently used by child and adolescent psychiatric clinics to diagnose, evaluate, and collect information and data. The tools allow professional physicians to assess if patients need further treatment, following a thorough and careful clinical diagnosis process.

**Objective:** We aim to determine potential indicators extracted from a mobile electroencephalography (EEG) device (Mindset; NeuroSky) and an actigraph (MotionWatch 8; CamNtech) and to validate them for diagnosis of ADHD. The 3 indicators are (1) attention, measured by the EEG; (2) meditation, measured by the EEG; and (3) activity, measured by the actigraph.

**Methods:** A total of 63 participants were recruited. The case group comprised 40 boys and 9 girls, while the control group comprised 5 boys and 9 girls. The groups were age matched. The test was divided into 3 stages—pretest, in-test, and posttest—with a testing duration of 20 minutes each. We used correlation analysis, repeated measures analysis of variance, and regression analysis to investigate which indicators can be used for ADHD diagnosis.

**Results:** With the EEG indicators, the analysis results show a significant correlation of attention with both hit reaction time (RT) interstimulus interval (ISI) change ($r$=–0.368; $P$=.003) and hit standard error (SE) ISI change ($r$=–0.336; $P$=.007). This indicates that the higher the attention of the participants, the smaller both the hit RT change and the hit SE ISI change. With the actigraph indicator, confidence index ($r$=0.352; $P$=.005), omissions ($r$=0.322; $P$=.01), hit RT SE ($r$=0.393; $P$=.001), and variability ($r$=0.351; $P$=.005) were significant. This indicates that the higher the activity amounts, the higher the impulsive behavior of the participants and the more target omissions in the continuous performance test (CPT). The results show that the participants with ADHD present a significant difference in activity amounts ($P$<0.001). The actigraph outperforms the EEG in screening ADHD.

**Conclusions:** When the participants with ADHD are stimulated under restricted conditions, they will present different amounts of activity than in unrestricted conditions due to participants' inability to exercise control over their concentration. This finding could be a new electronic physiological biomarker of ADHD. An actigraph can be used to detect the amount of activity exhibited and to help physicians diagnose the disorder in order to develop more objective, rapid auxiliary diagnostic tools.

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**KEYWORDS**

actigraphy; ADHD; attention deficit disorder with hyperactivity; clinical decision-making; electroencephalography; neuropsychological tests

## Introduction

Children with attention-deficit/hyperactivity disorder (ADHD), a neurobehavioral disorder, display behaviors of inattention, hyperactivity, or impulsivity, which can affect their ability to learn and establish proper family and social relationships. Children with ADHD can develop depression or behavioral problems, such as oppositional defiant disorder and conduct disorder [1]. Furthermore, children with ADHD may develop comorbid conditions like Tourette syndrome, learning disabilities, emotional disorders, sleep disorders, and anxiety disorders. Such comorbidities can aggravate ADHD, and these children may become more difficult to discipline and may appear to defy adults, annoy others deliberately, and show ill temper and other poor behavior; they may even become more difficult to treat [2,3].

Currently, diagnostic assessments such as the Wechsler Intelligence Scale for Children, computer-operated continuous performance test (CPT), the Gordon Diagnostic System (GDS) (Gordon Systems Inc), and the Wisconsin Card Sorting Test (Psychological Assessment Resources Inc) are used by child and adolescent psychiatric outpatient departments in hospitals [4,5]. In these assessments, parents are asked to respond to the child's behavior using a Swanson, Nolan and Pelham scale. The rating scale used by physicians to diagnose ADHD is mainly based on the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V) diagnostic criteria. Patients can only be correctly diagnosed through multiple information sources, including the physician's clinical evaluation, supplementary computer tests, scales filled out by their parents and teachers, a psychologist's assessment, and outpatient observation symptoms, among other tools.

Many years ago, the activity recorder became prominent in our daily lives, from the early development of the simple pedometer to the current more sophisticated exercise tracker and activity intensity recorder. Wearers use these for daily activity management and medical assessment to measure and understand their quantitative body energy consumption, record behavior, and assess sleep quality. Medical-grade recorders have been used by many researchers to record the activities of the wearer's circadian rhythm, as well as to help physicians by providing comparative and analytical behavioral patterns to understand objective sleep quality [6-12].

Brainwaves, on the other hand, can be used as a medical tool for carrying out differential diagnosis and to help physicians diagnose or exclude several illnesses [13-15]. They help provide an objective and more rapid understanding of the physical and mental status of individual patients. The brain is composed of neurons that perform electrical conduction activities while we think, imagine, observe, and perform many other mental activities, which produce weak electromagnetic waves. To observe these brain waves, a noninvasive brain wave acquisition method is used that amplifies brain waves with the help of electrode chips.

Diagnosing ADHD is time-consuming and can be complicated, as parents often need to make an appointment and schedule a hospital visit. As the development of the brain wave and activity recorder has gradually matured, it has become necessary to look for relevant indicators in brain waves and activity amounts in children with ADHD. Despite the current CPT, Test of Variables of Attention, GDS, and other auxiliary diagnostic tools, more convenient assessment tools are still needed. Furthermore, as the tests are boring, the process cannot be conducted if a child is not willing to cooperate. Therefore, the purpose of this study is to develop a more objective and faster assessment tool with electroencephalography (EEG) and actigraphy.

## Methods

### Research Tools

This study aims to explore the relationships among brain waves, activity amounts, and CPT indicators through a correlation analysis. The CPT [16] was used as the assessment tool to obtain various indicators of ADHD diagnosis reports, a mobile EEG device (MindSet; NeuroSky) [17] was used to obtain attention and meditation values in brain waves, and an actigraph (MotionWatch 8; CamNtech) was used to obtain information about activity amounts in the test. There have been a lot of studies focusing on detecting the attention and meditation values from EEG [18-21]. Attention is defined as the state of focus on relevant aspects of the environment, while meditation is defined as the state of relaxation in both the body and the mind.

The CPT is a set of assessment tools that use the computer as a platform. Children aged 6 to 12 years were recruited as research participants. The actigraph [22] was worn on the nondominant hand to cope with the use of similar sleep recorders.

### Study Design

#### *Participants*

This study was conducted with the permission of the Institutional Review Board of Chang Gung Memorial Hospital (No. 104-5397B). We defined an $\alpha$ of .05, power of 0.8, and effect size of Cohen $d$=0.8 for correlation analysis. The sample size of 12 was determined using G*Power (version 3.1.9.4; Heinrich-Heine-Universität Düsseldorf).

The participants and their parents signed the written consent form. The study was conducted from September 24, 2015, to September 23, 2016. A total of 63 participants, 45 boys and 18 girls, completed the test. The case group consisted of 49 participants with ADHD diagnosed by professional physicians. Participants were divided into a case group or control group depending on diagnosis of ADHD, and the groups were age matched.

### Diagnosis Determination and Acceptance Criteria

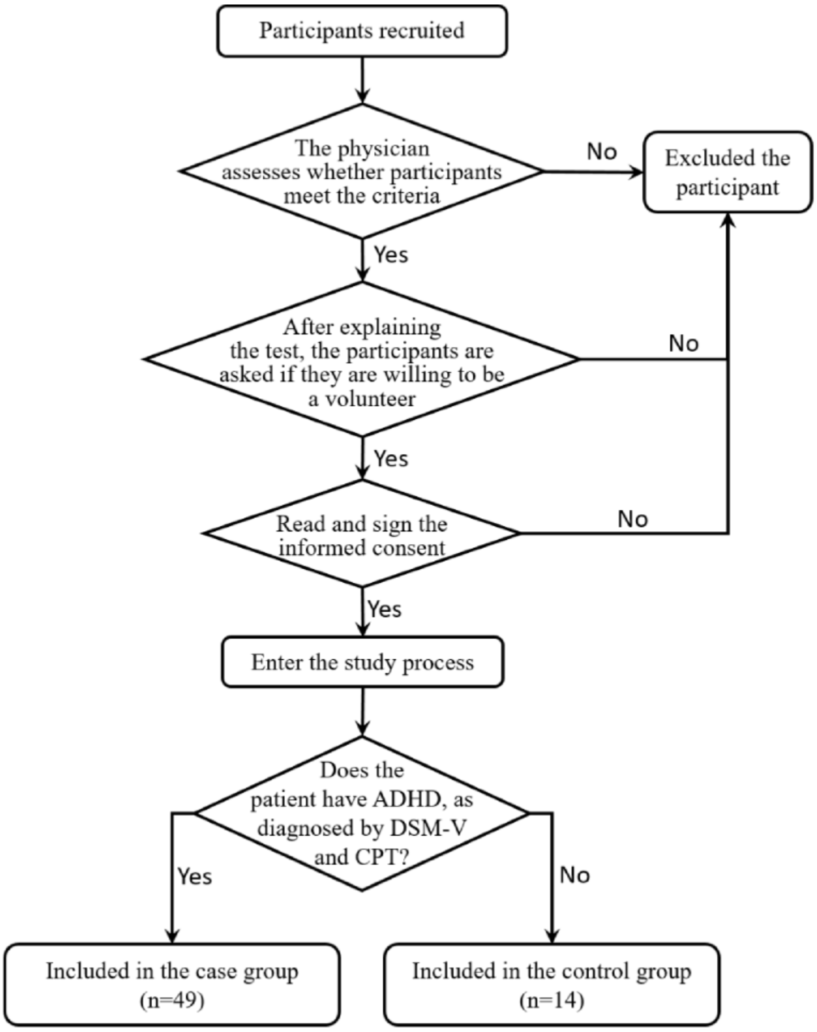
In this study, participants were recruited from the hospital's outpatient department and from elementary school. All participants were diagnosed and screened by professional pediatric psychiatrists, as shown in Figure 1.

The case group was made up of children with ADHD. The inclusion criteria were (1) participants who were willing to stop taking any psychotropic drugs or drugs that would affect the detection of cognitive functions 7 days before the test, (2) participants who could stabilize their emotions during the test, (3) participants who had been diagnosed with ADHD based on a CPT, and (4) participants who wanted to voluntarily participate in the test and had already signed a written consent form.

The control group was made up of children aged 6 to 12 years without ADHD who had normal growth development. The inclusion criteria were (1) participants who had not consumed any drugs that would affect the detection of cognitive functions 7 days prior to the test, (2) participants who could stabilize their emotions during the test, (3) participants who had taken a CPT and were found not to have ADHD, and (4) participants who wanted to voluntarily participate in the test and had already signed a written consent form.

The exclusion criteria for both the case group and the control group were (1) participants with low intelligence (a full intelligence quotient less than 70 points, as diagnosed by physicians); (2) participants with major brain diseases, severe psychiatric disorders, drug abuse, physical disabilities, or physical illnesses; (3) participants who had consumed drugs that would affect the cognitive functions measured by the test in the past 7 days; and (4) participants who did not sign the consent form.

**Figure 1.** Flow chart of the participant inclusion and exclusion process. ADHD: attention-deficit/hyperactivity disorder. CPT: continuous performance test. DSM-V: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition.



### *Study Design and Evaluation*

In this study, there were 63 participants, aged 6 to 12 years in 2 age-matched groups. Mean age, standard deviation, and a significance test are shown in Table 1.

The hardware used in the study was (1) a mobile EEG device, (2) a notebook computer, and (3) an actigraph. The software used in this study included (1) Windows 7 (Microsoft Corp), (2) ThinkGear Connector (NeuroSky), (3) Visual Studio 2010 (Microsoft Corp), (4) an actigraph resolution program (CamNtech), and (5) CPT II (Pearson Education).

**Table 1.** Descriptive statistics of the participants.

| Characteristic | Case group (n=49) | Control group (n=14) | *P* value |
|---|---|---|---|
| Age, mean (SD) | 8.69 (1.71) | 8.18 (1.84) | .36 |
| **Gender** | | | |
| Male, n (%) | 40 (82) | 5 (36) | |
| Female, n (%) | 9 (18) | 9 (64) | |

The tests on the participants were administered by assistants, psychiatrists, and graduate students at National Taipei University of Nursing and Health Sciences. They received complete CPT standard training on the test procedures under the guidance of physicians, and all of them understood the test operating system and examiner guidelines. The examiner guidelines were (1) give clear guidance using clear language and ensure that participants can understand; (2) unless necessary, do not talk to the participants during the test; (3) if encountering a participant with severe hyperactive symptoms, use a persuasive manner to prevent them from standing up and leaving the test site; and (4) should any incident occur during the test process, the safety of the participants is the priority.

### *Research Process*

The tests were conducted individually. Taking a total of 1 hour, the whole process was divided into 3 stages of 20 minutes each. Attention and meditation brain waves were recorded and activity levels were measured during all 3 stages. The test procedures for the case and control groups were the same. To reduce unnecessary interference, mobile phones, desktop computers, and other electronic equipment were turned off throughout the entire test. The study assessed brain waves and activity amounts in both the test with stimulation (stage 2) and the tests without stimulation (stage 1 and stage 3).

In stage 1 (pretest without stimulation), a parent brought the child to the test site and listened to a briefing about the test process. The participant was then helped to put on wearable devices to collect data from both the EEG and the actigraph, and the participant's parent was asked to fill out the scale form to complete the pretest preparation. This was a free activity environment.

In stage 2 (in-test with stimulation), data were continuously collected while the participants were stimulated by the CPT. This was a test environment.

In stage 3 (posttest without stimulation), data were continuously collected after the CPT. The participants completed the test, the scale forms were collected from the parents, and the wearable devices were taken off of the participants. This was a free activity environment.

### Statistical Methods

Statistical analyses were performed using IBM SPSS 22.0. We conducted correlation analysis to compare the values collected from the EEG and the actigraph to the CPT parameters of impulsivity, alertness, etc. We conducted repeated measures of analysis of variance (ANOVA) for interaction effects and post hoc analysis for differences. To investigate the confounding effect, we applied regression analysis. The threshold of significance was preset to *P*=.05.

## *Results*

### Correlation Analysis

Correlation analysis was completed to assess the values extracted from the tools (the EEG's brain waves and the actigraph's activity amounts) and to validate the CPT indicators for diagnosis of ADHD in stage 2. Table 2 shows the correlation coefficient (*r*) between CPT indicators, EEG values, and actigraph values. With the EEG, correlation analysis only shows a significant correlation of attention with hit reaction time (RT) interstimulus interval (ISI) change (*r*=–0.368; *P*=.003) and hit standard error (SE) ISI change (*r*=–0.336; *P*=.007). This indicates that the higher the attention of the participants, the smaller both the hit RT change and the hit SE ISI change. With the actigraph, there is significant correlation of activity levels with 4 indicators: confidence index (CI) (*r*=0.353; *P*=.005), omissions (*r*=0.322; *P*=.01), hit RT standard error (*r*=0.393; *P*=.001), and variability (*r*=0.351; *P*=.005). This indicates that the higher the activity amounts, the higher the impulsive behavior of the participants and the more target omissions in the CPT. CI that fits clinical diagnosis is significant. As a result, the participants may possibly be screened for ADHD with an actigraph.

**Table 2.** Correlation of indicators between CPT, EEG, and actigraph in stage 2.

| CPT[a] indicator | Sensor | | | | | |
|---|---|---|---|---|---|---|
| | EEG attention | | EEG meditation | | Actigraph activity | |
| | *r* | *P* value | *r* | *P* value | *r* | *P* value |
| CI | –0.215 | .09 | 0.053 | .68 | 0.353 | .005 |
| Omissions | –0.012 | .92 | –0.054 | .68 | 0.322 | .01 |
| Commissions | –0.045 | .73 | –0.086 | .50 | 0.081 | .53 |
| Hit RT[b] | –0.230 | .07 | 0.208 | .10 | 0.169 | .19 |
| Hit RT SE | –0.244 | .05 | 0.041 | .75 | 0.393 | .001 |
| Variability | –0.216 | .09 | –0.106 | .41 | 0.351 | .005 |
| Detectability (d') | –0.050 | .70 | –0.095 | .46 | 0.137 | .29 |
| Response Style (β) | –0.044 | .73 | 0.066 | .61 | 0.126 | .33 |
| Perseverations | –0.125 | .33 | –0.105 | .41 | 0.199 | .12 |
| Hit RT block change | –0.135 | .29 | 0.073 | .57 | 0.161 | .21 |
| Hit SE block change | –0.164 | .20 | –0.111 | .39 | 0.180 | .16 |
| Hit RT ISI[c] change | –0.368 | .003 | 0.029 | .82 | 0.241 | .06 |
| Hit SE ISI change | –0.336 | .007 | –0.046 | .72 | 0.200 | .12 |

[a] CPT: continuous performance test.

[b] RT: reaction time.

[c] ISI: interstimulus interval.

## Repeated Measures ANOVA

Based on the results of correlation analysis, the participants can be screened for ADHD by the activity indicator. In order to confirm the discrimination ability of the indicator, we conducted repeated measures ANOVA. Table 3 conforms to a spherical pattern in the within-subject test (*P*=.37). Table 4 shows significance with both within-subject (*P*<.001) and between-subject (*P*=.04) designs and no interaction effect between the group and the stage (*P*=.77).

We also conducted a post hoc test. Table 5 demonstrates significant difference between the 2 groups in the 3 stages. For the case group, there were significant differences among the three stages (stage 3>stage 1>stage 2), while only stage 2 differences were significant in the control group (stage 3=stage 1>stage 2). The analysis results show that the participants with ADHD can be screened because the difference in activity amounts is significant.

**Table 3.** Mauchly's test of sphericity in within-subject test[a].

| Group | Mean (SD) | | |
|---|---|---|---|
| | Stage 1 | Stage 2 | Stage 3 |
| Case (n=49) | 6.717 (2.949) | 1.795 (1.309) | 7.562 (2.918) |
| Control (n=14) | 5.530 (2.381) | 0.911 (0.436) | 6.057 (2.838) |

[a] *P*=.37.

**Table 4.** Significance of the activity indicator in the 3 stages with respect to group.

| Source | Sum of square | Mean square | *F* (*df*) | *P* value |
|---|---|---|---|---|
| **Subject** | | | | |
| Group | 46.183 | 46.183 | 4.632 (1,61) | .04 |
| Residual | 608.22 | 9.971 | N/A[a] | N/A |
| **Stage** | | | | |
| Stage | 770.011 | 385.005 | 97.644 (2,122) | <.001 |
| Group×stage | 2.101 | 1.051 | 0.266 (2,122) | .77 |
| Residual | 481.042 | 3.943 | N/A | N/A |
| Sum | 1907.557 | N/A | N/A | N/A |

[a] N/A: not applicable.

**Table 5.** Post hoc test after repeated measures ANOVA.

| Group, Stage I, and Stage J | Mean difference | *P* value |
|---|---|---|
| **Case**[a] | | |
| **1** | | |
| 2 | 4.922 | <.001 |
| 3 | –0.845 | .03 |
| **2** | | |
| 1 | –4.922 | <.001 |
| 3 | –5.767 | <.001 |
| **3** | | |
| 1 | 0.845 | .03 |
| 2 | 5.767 | <.001 |
| **Control**[b] | | |
| **1** | | |
| 2 | 4.627 | <.001 |
| 3 | –0.519 | .54 |
| **2** | | |
| 1 | –4.627 | <.001 |
| 3 | –5.146 | <.001 |
| **3** | | |
| 1 | 0.519 | .54 |
| 2 | 5.146 | <.001 |

[a] Stage 3>stage 1>stage 2.

[b] Stage 3=stage 1>stage 2.

## Regression Analysis

To investigate whether there are any confounders, we also applied regression analysis. We built 4 regression models ($M_i$, $i$=1-4). Each of them consecutively adds factor(s) to the model based on the previous one. The definition of $M_i$ is shown as follows, in which $y$ denotes the dependent variable of the activity value, $b_j$ ($j$=0-5) are coefficients of the models, and $r$ is residue. In addition, *group* is given to be a control variable and *stim* (stimulation, or the CPT) is given to be an independent variable.

There are 2 potential confounders: *age* and *gender*. Table 6 shows that both the *group* and the *stim* are the only factors affecting the activity value ($M_2$), and that there are no confounders in this study ($M_3$ and $M_4$).

$$M_1 : y = b_0 + b_1(group) + r$$

$$M_2 : y = b_0 + b_1(group) + b_2(stim) + r$$

$$M_3 : y = b_0 + b_1(group) + b_2(stim) + b_3(age) + b_4(gender) + r$$

$$M_4 : y = b_0 + b_1(group) + b_2(stim) + b_3(age) + b_4(gender) + b_5(age * gender) + r$$

**Table 6.** Regression models of the activity value respective to other variables.

| Variable | Regression model | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $M_1$ | | $M_2$ | | $M_3$ | | $M_4$ | |
| | Coefficient | *P* value | Coefficient | *P* value | Coefficient | *P* value | Coefficient | *P* value |
| Control: group | –.0141 | .052 | –0.141 | .006 | –0.181 | .001 | –0.182 | .001 |
| Independent: stim[a] | N/A[b] | N/A | –0.707 | <.001 | –0.707 | <.001 | –0.707 | <.001 |
| **Confounder** | | | | | | | | |
| Age | N/A | N/A | N/A | N/A | –0.056 | .273 | –0.057 | .265 |
| Gender | N/A | N/A | N/A | N/A | –0.079 | .158 | –0.080 | .154 |
| Interaction: $Z_{age}*Z_{gender}$ | N/A | N/A | N/A | N/A | N/A | N/A | –.018 | .722 |
| $R^2$ | 0.020 | N/A | 0.520 | N/A | 0.528 | N/A | 0.528 | N/A |
| $\Delta R^2$ | 0.020 | N/A | 0.500 | N/A | 0.008 | N/A | 0.000 | N/A |
| *F* (*df*) | 3.814<br>(1,187) | .052 | 193.418<br>(1,186) | <.001 | 1.592<br>(2,184) | .206 | 0.127<br>(1,183) | .722 |

[a] *stim*: stimulation.

[b] N/A: not applicable.

## Discussion

This is a case-control study, but there are some limitations. Sample size and gender in the case and control groups are unmatched. To deal with the limitations, the study recruited an age-matched sample for both case and control groups. In addition, as recommended by Faresjö and Faresjö [23], we conducted multivariate regression analyses, using *gender* and *group* as covariates and testing for significance of coefficients. The analysis result shows that *group* is the only factor affecting the activity value, and that *gender* is not a confounder in the study. This study is the first to use both brain waves and activity monitors to help the diagnosis of ADHD. When participants with ADHD performed the CPT, the study found the new electrophysiological biomarker collected by the activity sensor to be especially useful. The result shows that the actigraphy is an objective tool for the monitoring of activity in patients with ADHD, supporting previous findings that use actigraphy to understand the features of children with ADHD [24-28]. However, Muñoz-Organero et al [27] used an exam time of 6 school hours, while this study took only 20 minutes, which provides a better performance.

Analytical results showed that correlation of brain waves and CPT indicators is significant only for hit RT ISI change and hit SE ISI change. However, CI, which is the most important indicator to diagnose ADHD, was not related to the brain waves. The problem probably came from the device. The participants reflected that it is inconvenient to wear, so much so that they felt uncomfortable during the test. In addition, even though the device protects against noise interference, some data were still found to have interference from poor electrode contact. The source of the noise was caused by the loosening of the brain wave device. With the interference, the attention and meditation values could not be continuously recorded. Even though the results support that stimulus on participants with ADHD is a mediated factor of response capability, they are similar to the findings on stimulus discriminability (two-choice reaction time task) [29,30], in which the stimulus improved ADHD participants' task performance and ability to differentiate optimal from nonoptimal choices [30].

In the end, previous studies [31-33] revealed that participants with ADHD (case group) have inhibition deficits when compared with participants without ADHD (control group). However, in this study, ADHD participants presented lower activity in the stage with stimulus (the CPT) than in the stages without the stimulus. This implies that the extent of ADHD can be mediated by the stimulus. The study concludes that an activity recorder is a new electrophysiological biomarker that helps to diagnose ADHD. The use of an inappropriate recorder tends to get deviation results in activity values. Carefully selecting the recorder that can analyze the applicable scenarios and intensity of activities is vital. Furthermore, if the wearable device is worn on different parts of a person’s body, it will likely obtain different activity values. For future research, we suggest defining values for the threshold of activity for different ages, genders, and types of ADHD.

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## Conflicts of Interest

None declared.

## References

1. Tsai CH, Gau SF. Long-term outcome studies of hyperactive children: literature review. Kaohsiung J Med Sci 1999 Jun;15(6):307-314. [Medline: 10441937]
2. Norén Selinus E, Molero Y, Lichtenstein P, Larson T, Lundström S, Anckarsäter H, et al. Childhood Symptoms of ADHD Overrule Comorbidity in Relation to Psychosocial Outcome at Age 15: A Longitudinal Study. PLoS One 2015;10(9):e0137475 [FREE Full text] [doi: 10.1371/journal.pone.0137475] [Medline: 26360378]
3. von Gontard A, Equit M. Comorbidity of ADHD and incontinence in children. Eur Child Adolesc Psychiatry 2015 Feb;24(2):127-140. [doi: 10.1007/s00787-014-0577-0] [Medline: 24980793]
4. Achenbach TM, Howell CT, Quay HC, Conners CK. National survey of problems and competencies among four- to sixteen-year-olds: parents' reports for normative and clinical samples. Monogr Soc Res Child Dev 1991;56(3):1-131. [Medline: 1770964]
5. Applegate B, Lahey BB, Hart EL, Biederman J, Hynd GW, Barkley RA, et al. Validity of the age-of-onset criterion for ADHD: a report from the DSM-IV field trials. J Am Acad Child Adolesc Psychiatry 1997 Sep;36(9):1211-1221. [Medline: 9291722]
6. Garcia AW, Langenthal CR, Angulo-Barroso RM, Gross MM. A Comparison of Accelerometers for Predicting Energy Expenditure and Vertical Ground Reaction Force in School-Age Children. Measurement in Physical Education and Exercise Science 2004 Sep;8(3):119-144. [doi: 10.1207/s15327841mpee0803_1]
7. Jetté M, Sidney K, Blümchen G. Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity. Clin Cardiol 1990 Aug;13(8):555-565 [FREE Full text] [doi: 10.1002/clc.4960130809] [Medline: 2204507]
8. Paavonen EJ, Fjällberg M, Steenari MR, Aronen ET. Actigraph placement and sleep estimation in children. Sleep 2002 Mar 15;25(2):235-237. [doi: 10.1093/sleep/25.2.235] [Medline: 11902433]
9. Wiggs L, Montgomery P, Stores G. Actigraphic and parent reports of sleep patterns and sleep disorders in children with subtypes of attention-deficit hyperactivity disorder. Sleep 2005 Nov;28(11):1437-1445. [doi: 10.1093/sleep/28.11.1437] [Medline: 16335331]
10. Yesavage JA, Friedman L, Kraemer HC, Noda A, Wicks D, Bliwise DL, et al. A follow-up study of actigraphic measures in home-residing Alzheimer's disease patients. J Geriatr Psychiatry Neurol 1998;11(1):7-10. [doi: 10.1177/089198879801100103] [Medline: 9686746]
11. Lin C, Yang A, Su C. Objective measurement of weekly physical activity and sensory modulation problems in children with attention deficit hyperactivity disorder. Res Dev Disabil 2013 Oct;34(10):3477-3486. [doi: 10.1016/j.ridd.2013.07.021] [Medline: 23927990]
12. Elbaz M, Yauy K, Metlaine A, Martoni M, Leger D. Validation of a new actigraph motion watch versus polysomnography on 70 healthy and suspected sleep-disordered subjects. In: J Sleep Res. (Suppl 1). 2012 Presented at: The 21st Congress of the European Sleep Research Society; 4-8 September 2012; Paris, France p. 218.
13. Clarke AR, Barry RJ, McCarthy R, Selikowitz M. Age and sex effects in the EEG: differences in two subtypes of attention-deficit/hyperactivity disorder. Clin Neurophysiol 2001 May;112(5):815-826. [doi: 10.1016/s1388-2457(01)00487-4] [Medline: 11336897]
14. Ogrim G, Kropotov J, Hestad K. The quantitative EEG theta/beta ratio in attention deficit/hyperactivity disorder and normal controls: sensitivity, specificity, and behavioral correlates. Psychiatry Res 2012 Aug 15;198(3):482-488. [doi: 10.1016/j.psychres.2011.12.041] [Medline: 22425468]
15. Shi T, Li X, Song J, Zhao N, Sun C, Xia W, et al. EEG characteristics and visual cognitive function of children with attention deficit hyperactivity disorder (ADHD). Brain Dev 2012 Nov;34(10):806-811. [doi: 10.1016/j.braindev.2012.02.013] [Medline: 22459254]
16. Conners CK. Pearson Education. Conners' Continuous Performance Test (CPT II): version 5 for Windows: technical guide and software manual 2004 URL: https://www.pearsonclinical.co.uk/Psychology/ChildMentalHealth/ChildADDADHDBehaviour/ConnersContinuousPerformanceTestIIVersion5forWindows(CPTIIV5)/PDFReports/Profile.pdf [accessed 2020-05-11]
17. NeuroSky. NeuroSky Website. 2011 Mar 30. MindWave User Guide URL: http://developer.neurosky.com/docs/lib/exe/fetch.php?media=mindwave_user_guide_en.pdf [accessed 2020-05-12]

18. Liu N, Chiang C, Chu H. Recognizing the degree of human attention using EEG signals from mobile sensors. Sensors (Basel) 2013 Aug 09;13(8):10273-10286 [FREE Full text] [doi: 10.3390/s130810273] [Medline: 23939584]
19. Crowley K, Sliney A, Pitt I, Murphy D. Evaluating a Brain-computer interface to categorise human emotional response. Piscataway: IEEE; 2010 Presented at: Proceedings of 10th IEEE International Conference on Advanced Learning Technologies (ICALT); July 5-7, 2010; Sousse, Tunisia p. 276-278. [doi: 10.1109/icalt.2010.81]
20. Patsis G, Sahli H, Verhelst W, De Troyer O. Evaluation of Attention Levels in a Tetris Game Using a Brain Computer Interface. In: Proceedings of 21st International Conference, UMAP. Berlin Heidelberg: Springer; 2013 Presented at: 21st International Conference on User Modeling, Adaptation, and Personalization (UMAP); June 10-14, 2013; Rome, Italy p. 127-138. [doi: 10.1007/978-3-642-38844-6_11]
21. Vourvopoulos A, Liarokapis F. Evaluation of commercial brain–computer interfaces in real and virtual world environment: A pilot study. Computers & Electrical Engineering 2014 Feb;40(2):714-729. [doi: 10.1016/j.compeleceng.2013.10.009]
22. CamNtech. 2019 Mar 12. The MotionWatch and MotionWare User Guide, version 1.2.36a URL: https://www.camntech.com/images/products/MotionWatch/The%20MotionWatch%20User%20Guide.pdf [accessed 2020-05-11]
23. Faresjö T, Faresjö A. To match or not to match in epidemiological studies--same outcome but less power. Int J Environ Res Public Health 2010 Jan;7(1):325-332 [FREE Full text] [doi: 10.3390/ijerph7010325] [Medline: 20195449]
24. Melegari MG, Vittori E, Mallia L, Devoto A, Lucidi F, Ferri R, et al. Actigraphic Sleep Pattern of Preschoolers With ADHD. J Atten Disord 2020 Feb;24(4):611-624. [doi: 10.1177/1087054716672336] [Medline: 27708108]
25. Becker SP, Langberg JM, Eadeh H, Isaacson PA, Bourchtein E. Sleep and daytime sleepiness in adolescents with and without ADHD: differences across ratings, daily diary, and actigraphy. J Child Psychol Psychiatry 2019 Sep;60(9):1021-1031. [doi: 10.1111/jcpp.13061] [Medline: 31032953]
26. De Crescenzo F, Licchelli S, Ciabattini M, Menghini D, Armando M, Alfieri P, et al. The use of actigraphy in the monitoring of sleep and activity in ADHD: A meta-analysis. Sleep Med Rev 2016 Apr;26:9-20. [doi: 10.1016/j.smrv.2015.04.002] [Medline: 26163053]
27. Muñoz-Organero M, Powell L, Heller B, Harpin V, Parker J. Automatic Extraction and Detection of Characteristic Movement Patterns in Children with ADHD Based on a Convolutional Neural Network (CNN) and Acceleration Images. Sensors (Basel) 2018 Nov 14;18(11). [doi: 10.3390/s18113924] [Medline: 30441774]
28. O'Mahony N, Florentino-Liano B, Carballo JJ, Baca-García E, Rodríguez AA. Objective diagnosis of ADHD using IMUs. Med Eng Phys 2014 Jul;36(7):922-926. [doi: 10.1016/j.medengphy.2014.02.023] [Medline: 24657100]
29. Lúcio PS, Salum GA, Rohde LA, Swardfager W, Gadelha A, Vandekerckhove J, et al. Poor stimulus discriminability as a common neuropsychological deficit between ADHD and reading ability in young children: a moderated mediation model. Psychol Med 2017 Jan;47(2):255-266. [doi: 10.1017/S0033291716002531] [Medline: 27697085]
30. Sethi A, Voon V, Critchley H, Cercignani M, Harrison N. A neurocomputational account of reward and novelty processing and effects of psychostimulants in attention deficit hyperactivity disorder. Brain 2018 May 01;141(5):1545-1557. [doi: 10.1093/brain/awy048] [Medline: 29547978]
31. Albajara Sáenz A, Septier M, Van Schuerbeek P, Baijot S, Deconinck N, Defresne P, et al. ADHD and ASD: distinct brain patterns of inhibition-related activation? Transl Psychiatry 2020 Jan 22;10(1):24 [FREE Full text] [doi: 10.1038/s41398-020-0707-z] [Medline: 32066671]
32. Lipszyc J, Schachar R. Inhibitory control and psychopathology: a meta-analysis of studies using the stop signal task. J Int Neuropsychol Soc 2010 Nov;16(6):1064-1076. [doi: 10.1017/S1355617710000895] [Medline: 20719043]
33. Pievsky MA, McGrath RE. The Neurocognitive Profile of Attention-Deficit/Hyperactivity Disorder: A Review of Meta-Analyses. Arch Clin Neuropsychol 2018 Mar 01;33(2):143-157. [doi: 10.1093/arclin/acx055] [Medline: 29106438]

## Abbreviations

**ADHD:** attention-deficit/hyperactivity disorder
**ANOVA:** analysis of variance
**CI:** confidence index
**CPT:** continuous performance test
**DSM-V:** Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
**EEG:** electroencephalography
**GDS:** Gordon Diagnostic System
**ISI:** interstimulus interval change
**RT:** reaction time

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Original Paper

# Apps With Maps—Anxiety and Depression Mobile Apps With Evidence-Based Frameworks: Systematic Search of Major App Stores

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## Abstract

**Background:** Mobile mental health apps have become ubiquitous tools to assist people in managing symptoms of anxiety and depression. However, due to the lack of research and expert input that has accompanied the development of most apps, concerns have been raised by clinicians, researchers, and government authorities about their efficacy.

**Objective:** This review aimed to estimate the proportion of mental health apps offering comprehensive therapeutic treatments for anxiety and/or depression available in the app stores that have been developed using evidence-based frameworks. It also aimed to estimate the proportions of specific frameworks being used in an effort to understand which frameworks are having the most influence on app developers in this area.

**Methods:** A systematic review of the Apple App Store and Google Play store was performed to identify apps offering comprehensive therapeutic interventions that targeted anxiety and/or depression. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist was adapted to guide this approach.

**Results:** Of the 293 apps shortlisted as offering a therapeutic treatment for anxiety and/or depression, 162 (55.3%) mentioned an evidence-based framework in their app store descriptions. Of the 293 apps, 88 (30.0%) claimed to use cognitive behavioral therapy techniques, 46 (15.7%) claimed to use mindfulness, 27 (9.2%) claimed to use positive psychology, 10 (3.4%) claimed to use dialectical behavior therapy, 5 (1.7%) claimed to use acceptance and commitment therapy, and 20 (6.8%) claimed to use other techniques. Of the 162 apps that claimed to use a theoretical framework, only 10 (6.2%) had published evidence for their efficacy.

**Conclusions:** The current proportion of apps developed using evidence-based frameworks is unacceptably low, and those without tested frameworks may be ineffective, or worse, pose a risk of harm to users. Future research should establish what other factors work in conjunction with evidence-based frameworks to produce efficacious mental health apps.

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**KEYWORDS**

mHealth; apps; app store; depression; anxiety; e-mental health; smartphone; mobile mental health; digital mental health; mobile phone

## Introduction

### Background

The practice of psychotherapy is underpinned by evidence-based therapies and interventions. These techniques are used when they are proven to be efficacious via thorough experimental methods. In most developed countries, mental health clinicians are discouraged by professional associations and government regulations from using therapies without such evidence.

New technology is changing the way therapy can be delivered. Therapies previously only delivered face-to-face can now be accessed electronically, and the way that many people do this is via their smartphone. Smartphone apps are software programs that can be downloaded from specialist websites, known as app stores. The two biggest app stores are the Apple App Store and Google Play. Global expenditure on apps in 2018 was approximately US $92.1 billion [1], which attests to the widespread use of apps and value of smartphones to consumers.

### Mental Health: Is There an App for That?

Health, including mental health, apps are emerging as one of the most important categories of apps. A total of 75% of consumers believe that technology is important in managing their health, and 88% are willing to share mobile health (mHealth) data with their health care provider [2]. Approximately 48% of consumers are currently using a health app [2], and many more have downloaded at least one [3]. Health apps are in the top-10 list of worldwide categories for consumer spending on apps [4]. Although definitions about what constitutes a *health* app varies, and this influences the estimates of how many health apps are available, a 2017 report calculated that there were approximately 318,000 health apps available for download [5], with 10,000 of these relating to mental health [6].

People with mental illness are attracted to the possibility of utilizing apps to manage their mental health [7]; however, there is doubt in this population about how apps manage confidential information [8]. There is also uncertainty about the available functions of mental health apps and which apps are the most useful [9]. For guidance about what app to download, mental health consumers rely mainly on ratings and reviews in app stores [10] or on advice given through social media or word of mouth [11]. However, if a mental health expert is not involved in the development of an app, and if it has not been developed using an evidence-based theoretical framework, the app may not be effective or, worse, may do harm to its user.

There are many reasons why research on the efficacy of apps for anxiety and/or depression should be prioritized. Firstly, many people are already using mental health apps [6], and with five billion people around the world currently using a smartphone [12], there is potential for many more to do so in the future as this figure rises. Apps provide greater accessibility to mental health resources and offer instant mental health assistance. These features are especially relevant for traditionally difficult-to-reach cohorts, such as teenagers [13] and people in rural communities [14]. Mental health apps may also offer more cost-effective options for lower socioeconomic groups [15] and greater anonymity and flexibility for others. For example, using an app may be more convenient for consumers with limited time to access other therapy, and more convenient for clinicians who may prefer their clients and patients to do homework activities on their smartphone so that results can be digitally sent back to the clinician. Certain clients in therapy may also just prefer the novel value of doing interactive homework activities on their phone, rather than with a pen and paper. For many people, being able to use their phone for such activities is simply more convenient (eg, it may be easier for them to use a smartphone to do homework while they are travelling on a bus rather than handling awkward pieces of paper in such situations). In this way, apps may be used as adjuncts to other therapies. Apps can also be used in more practical ways, such as setting reminders to assist with treatment and medication compliance. All of these factors create the potential for apps to reduce the burden on existing mental health services [16].

### Apps and Evidence-Based Frameworks

For a mental health app to be efficacious, it is fundamental that it be underpinned by an evidence-based framework; that is, an established therapy technique for reducing psychological distress, such as cognitive behavioral therapy (CBT). An evidence-based framework provides a road map or blueprint for an app’s functions and performance. However, even when an app claims to offer CBT, the contents and functioning of the app may not align with CBT principles [17], especially if the app has been developed without expert input.

To date, there has been little research that addresses the potential harm a mental health app may do to an individual. It seems conceivable, however, that an app developed without a proven theoretical framework and method of intervention could have the potential to do harm to a user [18]. For instance, a recommendation to use herbal supplements could adversely interact with prescribed medication.

Over the last two decades, e-mental health programs with a CBT framework and designed for use on computers have been found to be effective for both adults and children in reducing anxiety and depression [19,20] and improving happiness and well-being [21-23]. Some studies have compared the effectiveness of e-mental health programs with face-to-face therapy and have found comparable [24,25], and, in some cases, even more favorable, results [26]. There is now an interest in how stand-alone apps for smartphones (ie, programs that can be downloaded and used without an internet connection) based on CBT or other evidence-based theoretical frameworks may further enhance a clinician’s digital toolbox [27].

CBT proposes that emotions can be more effectively managed by adjusting thinking and behavior and recognizing physiological responses [28]. CBT has an established evidence base and history of successfully treating anxiety and depression, both in individual therapy [29] and in group settings [30]. The CBT framework offers a broad range of efficacious interventions [31], including the following: the use of *thought diaries* to challenge negative thinking; coming up with personally meaningful affirmations; different types of physical exercise, such as walking and dancing; increasing social connectedness and having personally meaningful social interaction; increasing the amount of time doing pleasurable, or once pleasurable, activities; structured problem solving; and others. Many of these CBT interventions have been incorporated into mental health apps.

Other therapies that have been developed from traditional CBT have also been used successfully to treat anxiety and depression. Positive psychology, for instance, has become a more recent framework that is, under a strict definition, a type of CBT but has a different focus. Rather than simply *fixing* psychopathology, positive psychology aims to help individuals reach their full well-being potential by increasing optimism and happiness [32]. Studies on various positive psychology interventions have revealed efficacious empirical support for reducing symptoms of anxiety and depression as well as increasing well-being and happiness. For example, Freedman and Enright [33] showed that forgiveness significantly decreased depression, Froh et al [34] implemented a gratitude intervention that resulted in significantly greater optimism and life satisfaction as well as decreased negative affect, Lyubomirsky et al [35] reported an increase in happiness and well-being for participants who completed acts of kindness, and Seligman et al [36] successfully used three strategies to increase happiness and decrease depressive symptoms: (1) using one's signature strengths in new ways, (2) writing down three positive things each day, and (3) writing a letter of gratitude. All of these interventions could conceivably be incorporated into mental health apps and most already have.

Similarly, other frameworks, often referred to as third-wave therapies [37], have offered up interventions that are suitable for use in mental health apps. Various mindfulness interventions have proved efficacious in the past [38], and these meditation and breathing activities are easily incorporated into an app. Dialectical behavior therapy (DBT) is an intersection of various interventions, including mindfulness, distress tolerance, emotional regulation, and improving social relatedness activities. These may involve dialectical interaction with a therapist, including recording distress ratings, among other interventions that have proven effective in reducing symptoms of anxiety and/or depression, with particular focus on individuals with a diagnosis of borderline personality disorder [39]. Interpersonal therapy (IPT) involves interventions designed to improve current interpersonal relationships and social dysfunction, rather than focusing on personality, as an efficacious way of improving symptoms of depression [40]. Acceptance and commitment therapy (ACT) focuses on an individual accepting distressing thoughts and performing committed actions guided by one's values; ACT has proven efficacious for both anxiety [41] and depression [42]. All the frameworks listed here potentially comprise interventions that may conceivably be incorporated into an app.

### Objectives of This Study

This study involved a systematic search of app stores and concentrated on apps that offered a comprehensive therapeutic treatment for anxiety and/or depression, as opposed to apps that may offer singular or novel interventions (see *inclusion criteria* in the Methods section for more details about this definition). The research questions were as follows: (1) What proportion of publicly available apps offering a therapeutic treatment for anxiety and/or depression have used an evidence-based framework in their development? and (2) In an effort to understand which specific frameworks are having the most influence on mental health app developers, what are the proportions of specific frameworks? No previous study or review could be located that examined this issue by focusing on publicly available apps listed in the app stores.

## Methods

This systematic review used the AMSTAR (A MeaSurement Tool to Assess systematic Reviews) 2 [43] and PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [44] protocols for guidance in conducting the app store search. Although these protocols were developed specifically for literature searches, they offer appropriate direction that can be applied to searching app stores in the absence of such a specific guide. However, there are limitations in their use for guidance in app store searches. We adapted both of these protocols into a unique protocol and checklist specifically for app store searches: the Protocol for App Store Systematic Reviews (PASSR) checklist is a combination and reworking of the items from AMSTAR 2 and PRISMA that can be applied to the systematic search of app stores for any category of apps. The same wording as used in both AMSTAR 2 and PRISMA has been retained wherever possible to enable ease of comparison (see Multimedia Appendix 1).

Four researchers, including the lead author (JMM), systematically searched the Apple App Store and Google Play store in December 2018, and then again in July 2019, to ensure newly available apps were included for review. These two marketplaces attract more than three times as much revenue from downloads as their next competitor, the Windows Store [45], and over 90% of available apps for depression can be found in either of these stores [46].

Searches in each marketplace were made with the following 19 keywords across all categories: mental health, depression, anxiety, wellbeing, happiness, psychological distress, positive psychology, suicide, mental illness, CBT, cognitive behaviour therapy, cognitive behavior therapy, ACT, acceptance and commitment therapy, DBT, dialectical behaviour therapy, dialectical behavior therapy, IPT, and interpersonal therapy.

Apps were shortlisted based on their app store descriptions, and apps that were available in both stores were only counted once.

Inclusion criteria were as follows:

1. The app language and store description are in English.
2. The app offers a therapeutic treatment for anxiety and/or depression, not just singular elements of a therapy, such as monitoring symptoms, recording thoughts, or diagnosing the disorder, although apps could have any of these as part of a therapeutic treatment. In this way, apps were excluded if they used only singular elements. This approach is in contrast to other similar reviews [27] that have identified apps with single tools rather than comprehensive treatments. Therapeutic treatment was defined for this study's purpose as "offering focused treatment suggestions specifically for

> reducing symptoms of anxiety and/or depression in a manner comprehensive enough to be considered a type of therapy."

## Results

A search of the Apple App Store and Google Play store uncovered a shortlist of 293 apps whose app store descriptions inferred that they offered a therapeutic treatment for anxiety and/or depression; the full list of these apps is available from the corresponding author (JMM). Of these 293 apps, a total of 162 (55.3%) claimed to have an evidence-based theoretical framework informing the app's development. Differences between the Apple App Store (112/197, 56.9%) and the Google Play store (50/96, 52%) were negligible.

The evidence-based frameworks found in the apps represented the following proportions: CBT, 30.0% (88/293); mindfulness, 15.7% (46/293); positive psychology, 9.2% (27/293); DBT, 3.4% (10/293); ACT, 1.7% (5/293); and others, 6.8% (20/293). Note, some apps claimed to use multiple frameworks—each time a framework was mentioned, it was counted.

When including only the 162 apps with a theoretical framework in the analysis, the breakdown was as follows: CBT, 54.3% (88/162); mindfulness, 28.4% (46/162); positive psychology, 16.7% (27/162); DBT, 6.2% (10/162); ACT, 3.1% (5/162); and others, 12.3% (20/162).

Of those 162 apps with evidence-based frameworks, 10 (6.2%) were found to have published evidence for their effectiveness (see Table 1). The nine research articles [47-55] that examined the 10 apps were made up of seven randomized controlled trials (RCTs)—the Flett et al article contained one RCT with 2 of the listed apps: *Headspace* and *Smiling Mind* [52]—and two feasibility or pilot studies: Kinderman et al [48] and Carey et al [55]. Total participant numbers were comprised of 1017 in intervention conditions and 447 in control groups. The mean age across those studies that provided enough information was 32.7 years (SD 9.3). Intervention phases fluctuated between 2 and 12 weeks. Three studies reported long-term follow-up, the longest period being 3 months (see Table 2 for a summary of research characteristics).

**Table 1.** Coding used for app store search, and the search results.

| Code | Description (ie, framework) | Apps with this framework (N=293), n (%) | Apps with published research, n (%) | Name of the app (or apps) with published research |
|---|---|---|---|---|
| CBT | Cognitive behavioral therapy | 88 (30.0) | 5/88 (6) | Agoraphobia Free<br>Catch It<br>PTSD Coach<br>MoodMission<br>Thought Challenger |
| MIND | Mindfulness | 46 (15.7) | 3/46 (7) | Headspace<br>Smiling Mind<br>DeStressify |
| POS | Positive psychology | 27 (9.2) | 1/27 (4) | SuperBetter |
| DBT | Dialectical behavior therapy | 10 (3.4) | 0 (0) | N/A[a] |
| ACT | Acceptance and commitment therapy | 5 (1.7) | 0 (0) | N/A |
| OTH | Other recognized framework | 20 (6.8) | 1/20 (5) | MindSurf |
| NONE | No theoretical framework | 131 (44.7) | 0 (0) | N/A |

[a] N/A: not applicable.

**Table 2.** Summary of published research for shortlisted apps.

| App name | Reference | Sample characteristics | Intervention period;<br>long-term follow-up period | Statistically significant improvements | Outcome measure used |
|---|---|---|---|---|---|
| Agoraphobia Free | Christoforou et al [47] | Intervention group: n=73<br>Control group: n=69<br>Mean age (SD): 39.7 years (11.3) | 12 weeks;<br>no follow-up | Anxiety | PAS[a] |
| Catch It | Kinderman et al [48] | Intervention group: n=285<br>Control group: none<br>Mean age (SD): 48.2 years (SD not given) | 6 weeks (but varied among participants);<br>no follow-up | *Positive* and *negative* mood | None[b] |
| PTSD Coach | Kuhn et al [49] | Intervention group: n=62<br>Control group: n=58<br>Mean age (SD): 39.3 years (14.6) | 3 months;<br>3 months | Anxiety and depression | PCL-C[c] and PHQ-9[d] |
| MoodMission | Bakker et al [50] | Intervention group (a): n=56<br>Intervention group (b): n=56<br>Intervention group (c): n=50<br>Control group: n=64<br>Mean age (SD): 34.2 years (12.1) | 30 days;<br>no follow-up | Depression | PHQ-9 |
| Thought Challenger | Stiles-Shields et al [51] | Intervention group (a): n=10<br>Intervention group (b): n=10<br>Control group: n=10<br>Mean age (SD): not given | 6 weeks;<br>4 weeks | Depression | PHQ-9 |
| Headspace | Flett et al [52] | Intervention group: n=67<br>Control group: n=67<br>Mean age (SD): 20.1 years (2.8) | 40 days;<br>no follow-up | Depression | CES-D[e] |
| Smiling Mind | Flett et al [52] | Intervention group: n=58<br>Control group: n=67<br>Mean age (SD): 20.1 years (2.8) | 40 days;<br>no follow-up | Depression | CES-D |
| DeStressify | Lee and Jung [53] | Intervention group: n=77<br>Control group: n=86<br>Mean age (SD): 20.6 years (SD not given) | 4 weeks;<br>no follow-up | Trait anxiety | STAI[f] |
| SuperBetter | Roepke et al [54] | Intervention group (a): n=93<br>Intervention group (b): n=97<br>Control group: n=93<br>Mean age (SD): 40.2 years (12.4) | 4 weeks;<br>6 weeks | Depression | CES-D |
| MindSurf | Carey et al [55] | Intervention group: n=23<br>Control group: none<br>Mean age (SD): not given | 2 weeks;<br>no follow-up | Anxiety and depression (not statistically significant) | DASS-21[g] |

[a] PAS: Panic and Agoraphobia Scale.

[b] Used direct data input from apps based on words used by users to describe mood.

[c] PCL-C: PTSD (posttraumatic stress disorder) Checklist – Civilian.

[d] PHQ-9: Patient Health Questionnaire – Depression Scale.

[e] CES-D: Center for Epidemiologic Studies – Depression Scale.

[f] STAI: State Trait Anxiety Inventory.

[g] DASS-21: Depression Anxiety Stress Scales – 21-Item Version.

## Discussion

### Principal Findings

The purpose of this study was to locate mobile mental health apps for treating anxiety and/or depression that contained recognized theoretical frameworks underpinning their development. A search of the Apple App Store and Google Play store revealed a total of 293 apps claiming to offer a therapeutic treatment for anxiety and/or depression, with just over half claiming to have been developed using an evidence-based theoretical framework. Of these, CBT was the most quoted framework in app store descriptions. The method used to identify these apps mimicked that of how a consumer in the general population would ordinarily locate an app to treat anxiety and/or depression; that is, by using the search function of an app store, then reading the description of each app.

CBT has a research history of over 60 years, longer than any of the other theoretical frameworks contained in the shortlisted apps [56]. It is widely known as being effective for a range of conditions, including cessation of smoking [57] and other drugs [58], managing pain [59], and relieving symptoms of mental ill-health across a range of psychological disorders [56]. CBT is also a term widely known across health-related settings and professions and is often used in information directed at the general community for public campaigns of ways to manage mental ill-health and stress [60]. It perhaps comes as no surprise, then, that CBT is the most widely used theoretical framework in apps for anxiety and depression. However, new research is accelerating in many of the other theoretical frameworks listed in this review [61]; it may be that the proportion of CBT-based apps lessens over time as a result.

The popularity of the term CBT, as well as the growing popularity of the terms used to identify the other evidence-based frameworks in this review, may be contributing to apps being developed by nonexperts who incorrectly quote these terms in app store descriptions as a means of attempting to gain legitimacy. There are no known safeguards in place anywhere in the world to stop this from happening. While government agencies have started to regulate the health app space, this regulation has thus far focused on apps that only pose a risk of harm to users [62]. While this is important and a welcome addition to the oversight of mental health apps, it does not provide checks on accuracy of information in app store descriptions of apps that may not fall into the category of posing a risk of harm. Such apps may provide fake or incorrect information that may, at worst, be ineffective at reducing anxiety or depression, but they may continue to be available in app marketplaces because they do not meet criteria that would identify them as posing a risk of harm to users. If an app claims to wrongly categorize its interventions as CBT, DBT, ACT, mindfulness, or positive psychology, one of the dangers is that such misuse of these terms may lead users to believe that such theoretical frameworks do not work if the user does not get any benefit from the app.

A detailed analysis of the research that accompanied 10 of the shortlisted apps is outside the scope of this paper, as this review is focused on the theoretical frameworks that underpin mental health apps. The quality and quantity of research into mental health apps has been detailed elsewhere [63-66]. However, the research found to accompany the apps listed here does appear to vary greatly in methodology; this reaffirms the claims of heterogeneity made in those literature reviews. These reviews all call for more research and ongoing evaluation of research methodology into studying apps, as the current methodologies may not be the most appropriate [62,67,68].

By examining evidence-based frameworks in mental health apps, this review has highlighted the high proportion (131/293, 44.7%) of apps that claim to offer a therapeutic treatment for anxiety and/or depression that do not rely on validated techniques. It is useful to think of an evidence-based theoretical framework as being like a map that guides clinicians in their therapeutic practices. This is at the heart of a clinician being effective in their treatment and, at the very least, not doing harm to their client or patient. While many mental health apps claim to be using an evidence-based theoretical framework, as many as 44.7% may not be; this leaves open the possibility, therefore, that a large proportion of these apps may be ineffective and possibly run the risk of doing the user harm.

## Limitations

This review of app stores suffers from the same limitation as other reviews of app stores: the restricted way that searches are conducted. The Apple App Store and Google Play store search results can be challenging because important information may be absent. How developers have completed online questionnaires prior to registering their app for public download, as well as the interaction of these with algorithms developed by the app store, determine the outcomes of a search. Consequently, there are differences in the order in which apps are presented when specific search terms are employed, and there are limited search functions compared to those available when performing a literature search. The results of an app store search are not necessarily presented in a logical order to users because they are unable to choose to display results according to multiple criteria, such as being able to filter from most recent to oldest, as one can do in a literature search. The outcome can lead to considerable ambiguity about the order of displayed results.

Another difference between a search of app stores and a search of the literature is that research may be found on a particular app, but that app may not be available for download to the general public. For example, Torous et al [27] discovered peer-reviewed publications on the efficacy of four CBT-based apps—excluding apps that were based on DBT or ACT—but when they searched the app stores for these apps, none could be found. While research is welcomed and encouraged in the development of mental health apps, in the end what matters most is how many of these efficacious apps are available to the general population.

Another limitation of this research is that results were based on the contents of descriptions in the app stores. None of the shortlisted apps were trialed to confirm that their description corresponded to actual content. For example, a nonexpert may have developed an app and claimed in the description that it used a CBT framework, but the developer may not have incorporated any genuine CBT interventions into the app functions. If such pseudo-CBT apps exist, it is likely that they will fail to assist users to manage anxiety and/or depression and may, therefore, lead consumers to believe that CBT is ineffective [27].

## Conclusions

This review has highlighted difficulties faced by clinicians and consumers when searching the app stores for an app that offers a therapeutic treatment for anxiety and/or depression. The limited search capabilities of the app stores make it difficult to find the most appropriate app for one's needs. If an individual wants to find a mental health app based on an evidence-based framework, it is difficult to sort through the many other apps that do not have that guiding framework.

Just as mental health clinicians are trained to follow evidence-based frameworks in their practice, it is reasonable to assume that mental health apps should do the same in their functioning. This review found that little more than half do, according to their app store descriptions. Just as successful therapeutic outcomes of face-to-face therapy can be attributed to more than the theoretical framework—factors such as rapport with the therapist, therapist skills, and an individual's motivation to change—so too are there other elements of a mental health app that may contribute to a successful therapeutic outcome, such as usability and ease of use, aesthetics, level of gamification, etc [65,69]. There would appear to be much research that still needs to be done on all these factors and how they interrelate with theoretical frameworks as well as whether certain factors mediate or moderate others.

Another suggested area of future research is to compare apps developed with evidence-based theoretical frameworks with their face-to-face equivalents. Clinicians and consumers need to know about the effectiveness and limitations of apps and where they sit alongside traditional evidence-based approaches. If clinicians and consumers become more confident in understanding how mental health apps can assist in reducing symptoms of anxiety and/or depression, it may increase the take-up of this new treatment modality and turn the potential advantages of using mental health apps into a reality.

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## Authors' Contributions

JMM wrote the manuscript drafts and supervised the app store review. DAD and WB proofread and edited the manuscript drafts and supervised the overall research project. All authors read and approved the final submitted version.

## Conflicts of Interest

None declared.

Multimedia Appendix 1
Protocol for App Store Systematic Reviews (PASSR).
[PDF File (Adobe PDF File), 147 KB - mental_v7i6e16525_app1.pdf ]

## References

1. Freier A. Business of Apps. Staines-upon-Thames, UK: Soko Media; 2018 Sep 13. App revenue reaches $92.1 billion in 2018 driven by mobile gaming apps URL: https://www.businessofapps.com/news/app-revenue-reaches-92-1-billion-in-2018-driven-by-mobile-gaming-apps/ [accessed 2020-06-09]
2. Accenture. New York, NY: Accenture; 2018. Meet today's healthcare team: Patients + doctors + machines - Accenture 2018 consumer survey on digital health URL: https://www.accenture.com/us-en/insight-new-2018-consumer-survey-digital-health?utm_source=newsletter&utm_medium=email&utm_campaign=newsletter_axiosvitals&stream=top-stories [accessed 2019-07-12]
3. Colder Carras M, Mojtabai R, Furr-Holden CD, Eaton W, Cullen BAM. Use of mobile phones, computers and internet among clients of an inner-city community psychiatric clinic. J Psychiatr Pract 2014 Mar;20(2):94-103 [FREE Full text] [doi: 10.1097/01.pra.0000445244.08307.84] [Medline: 24638044]
4. Sydow L. App Annie. New York, NY: App Annie; 2019 Jan 16. The state of mobile in 2019: The most important trends to know URL: https://www.appannie.com/en/insights/market-data/the-state-of-mobile-2019/ [accessed 2019-08-20]
5. IQVIA Institute. The Growing Value of Digital Health: Evidence and Impact on Human Health and the Healthcare System. Parsippany, NJ: IQVIA Institute for Human Data Science; 2017 Nov 07. URL: https://www.iqvia.com/institute/reports/the-growing-value-of-digital-health [accessed 2019-01-25]
6. Torous J, Firth J, Huckvale K, Larsen ME, Cosco TD, Carney R, et al. The emerging imperative for a consensus approach toward the rating and clinical recommendation of mental health apps. J Nerv Ment Dis 2018 Aug;206(8):662-666. [doi: 10.1097/NMD.0000000000000864] [Medline: 30020203]
7. Torous J, Powell AC. Current research and trends in the use of smartphone applications for mood disorders. Internet Interv 2015 May;2(2):169-173. [doi: 10.1016/j.invent.2015.03.002]
8. Hendrikoff L, Kambeitz-Ilankovic L, Pryss R, Senner F, Falkai P, Pogarell O, et al. Prospective acceptance of distinct mobile mental health features in psychiatric patients and mental health professionals. J Psychiatr Res 2019 Feb;109:126-132. [doi: 10.1016/j.jpsychires.2018.11.025] [Medline: 30530207]

9. Carpenter-Song E, Noel VA, Acquilano SC, Drake RE. Real-world technology use among people with mental illnesses: Qualitative study. JMIR Ment Health 2018 Nov 23;5(4):e10652 [FREE Full text] [doi: 10.2196/10652] [Medline: 30470681]
10. Huang H, Bashir M. Users' adoption of mental health apps: Examining the impact of information cues. JMIR Mhealth Uhealth 2017 Jun 28;5(6):e83 [FREE Full text] [doi: 10.2196/mhealth.6827] [Medline: 28659256]
11. Rubanovich CK, Mohr DC, Schueller SM. Health app use among individuals with symptoms of depression and anxiety: A survey study with thematic coding. JMIR Ment Health 2017 Jun 23;4(2):e22 [FREE Full text] [doi: 10.2196/mental.7603] [Medline: 28645891]
12. O'Dea S. Statista. New York, NY: Statista; 2019 Feb 28. Number of smartphone users worldwide from 2016 to 2021 (in billions) URL: https://www.statista.com/statistics/330695/numberof-smartphone-users-worldwide/ [accessed 2019-10-19]
13. Wang K, Varma DS, Prosperi M. A systematic review of the effectiveness of mobile apps for monitoring and management of mental health symptoms or disorders. J Psychiatr Res 2018 Dec;107:73-78. [doi: 10.1016/j.jpsychires.2018.10.006] [Medline: 30347316]
14. Jones N, Moffitt M. Ethical guidelines for mobile app development within health and mental health fields. Prof Psychol Res Pr 2016 Apr;47(2):155-162. [doi: 10.1037/pro0000069]
15. Smith A. Pew Research Center. Washington, DC: Pew Internet & American Life Project; 2015 Apr 01. Chapter one: A portrait of smartphone ownership URL: http://www.pewinternet.org/2015/04/01/chapter-one-a-portrait-of-smartphone-ownership/ [accessed 2019-01-20]
16. Newman MG, Szkodny LE, Llera SJ, Przeworski A. A review of technology-assisted self-help and minimal contact therapies for anxiety and depression: Is human contact necessary for therapeutic efficacy? Clin Psychol Rev 2011 Feb;31(1):89-103. [doi: 10.1016/j.cpr.2010.09.008] [Medline: 21130939]
17. Stawarz K, Preist C, Tallon D, Wiles N, Coyle D. User experience of cognitive behavioral therapy apps for depression: An analysis of app functionality and user reviews. J Med Internet Res 2018 Jun 06;20(6):e10120 [FREE Full text] [doi: 10.2196/10120] [Medline: 29875087]
18. Moshi MR, Tooher R, Merlin T. Suitability of current evaluation frameworks for use in the health technology assessment of mobile medical applications: A systematic review. Int J Technol Assess Health Care 2018 Jan;34(5):464-475. [doi: 10.1017/S026646231800051X] [Medline: 30201060]
19. Ebert DD, Zarski A, Christensen H, Stikkelbroek Y, Cuijpers P, Berking M, et al. Internet and computer-based cognitive behavioral therapy for anxiety and depression in youth: A meta-analysis of randomized controlled outcome trials. PLoS One 2015;10(3):e0119895 [FREE Full text] [doi: 10.1371/journal.pone.0119895] [Medline: 25786025]
20. Richards D, Richardson T. Computer-based psychological treatments for depression: A systematic review and meta-analysis. Clin Psychol Rev 2012 Jun;32(4):329-342. [doi: 10.1016/j.cpr.2012.02.004] [Medline: 22466510]
21. Davies EB, Morriss R, Glazebrook C. Computer-delivered and web-based interventions to improve depression, anxiety, and psychological well-being of university students: A systematic review and meta-analysis. J Med Internet Res 2014 May 16;16(5):e130 [FREE Full text] [doi: 10.2196/jmir.3142] [Medline: 24836465]
22. Manicavasagar V, Horswood D, Burckhardt R, Lum A, Hadzi-Pavlovic D, Parker G. Feasibility and effectiveness of a web-based positive psychology program for youth mental health: Randomized controlled trial. J Med Internet Res 2014 Jun 04;16(6):e140 [FREE Full text] [doi: 10.2196/jmir.3176] [Medline: 24901900]
23. Powell J, Hamborg T, Stallard N, Burls A, McSorley J, Bennett K, et al. Effectiveness of a web-based cognitive-behavioral tool to improve mental well-being in the general population: Randomized controlled trial. J Med Internet Res 2012 Dec 31;15(1):e2 [FREE Full text] [doi: 10.2196/jmir.2240] [Medline: 23302475]
24. Andrews G, Cuijpers P, Craske MG, McEvoy P, Titov N. Computer therapy for the anxiety and depressive disorders is effective, acceptable and practical health care: A meta-analysis. PLoS One 2010 Oct 13;5(10):e13196 [FREE Full text] [doi: 10.1371/journal.pone.0013196] [Medline: 20967242]
25. Richardson T, Stallard P, Velleman S. Computerised cognitive behavioural therapy for the prevention and treatment of depression and anxiety in children and adolescents: A systematic review. Clin Child Fam Psychol Rev 2010 Sep;13(3):275-290. [doi: 10.1007/s10567-010-0069-9] [Medline: 20532980]
26. Merry SN, Stasiak K, Shepherd M, Frampton C, Fleming T, Lucassen MFG. The effectiveness of SPARX, a computerised self help intervention for adolescents seeking help for depression: Randomised controlled non-inferiority trial. BMJ 2012 Apr 18;344:e2598 [FREE Full text] [doi: 10.1136/bmj.e2598] [Medline: 22517917]
27. Torous J, Levin ME, Ahern DK, Oser ML. Cognitive behavioral mobile applications: Clinical studies, marketplace overview, and research agenda. Cogn Behav Pract 2017 May;24(2):215-225. [doi: 10.1016/j.cbpra.2016.05.007]
28. Beck AT, Rush AJ, Shaw BF, Emery G. Cognitive Therapy of Depression. New York, NY: Guilford Press; 1979.
29. Butler AC, Chapman JE, Forman EM, Beck AT. The empirical status of cognitive-behavioral therapy: A review of meta-analyses. Clin Psychol Rev 2006 Jan;26(1):17-31. [doi: 10.1016/j.cpr.2005.07.003] [Medline: 16199119]
30. McDermut W, Miller IW, Brown RA. The efficacy of group psychotherapy for depression: A meta-analysis and review of the empirical research. Clin Psychol Sci Pract 2001;8(1):98-116. [doi: 10.1093/clipsy.8.1.98]
31. Bennett-Levy J, Richards D, Farrand P, Christensen H, Griffiths K, Kavanagh D, et al, editors. Oxford Guide To Low Intensity CBT Interventions. New York, NY: Oxford University Press; 2010.

32. Seligman MEP, Csikszentmihalyi M. Positive psychology: An introduction. Am Psychol 2000;55(1):5-14. [doi: 10.1037//0003-066x.55.1.5]
33. Freedman SR, Enright RD. Forgiveness as an intervention goal with incest survivors. J Consult Clin Psychol 1996;64(5):983-992. [doi: 10.1037/0022-006x.64.5.983]
34. Froh JJ, Sefick WJ, Emmons RA. Counting blessings in early adolescents: An experimental study of gratitude and subjective well-being. J Sch Psychol 2008 Apr;46(2):213-233. [doi: 10.1016/j.jsp.2007.03.005] [Medline: 19083358]
35. Lyubomirsky S, Sheldon KM, Schkade D. Pursuing happiness: The architecture of sustainable change. Rev Gen Psychol 2005 Jun;9(2):111-131. [doi: 10.1037/1089-2680.9.2.111]
36. Seligman MEP, Steen TA, Park N, Peterson C. Positive psychology progress: Empirical validation of interventions. Am Psychol 2005;60(5):410-421. [doi: 10.1037/0003-066X.60.5.410] [Medline: 16045394]
37. Hayes SC, Hofmann SG. The third wave of cognitive behavioral therapy and the rise of process-based care. World Psychiatry 2017 Oct;16(3):245-246 [FREE Full text] [doi: 10.1002/wps.20442] [Medline: 28941087]
38. Hofmann SG, Sawyer AT, Witt AA, Oh D. The effect of mindfulness-based therapy on anxiety and depression: A meta-analytic review. J Consult Clin Psychol 2010 Apr;78(2):169-183 [FREE Full text] [doi: 10.1037/a0018555] [Medline: 20350028]
39. Lynch TR, Chapman AL, Rosenthal MZ, Kuo JR, Linehan MM. Mechanisms of change in dialectical behavior therapy: Theoretical and empirical observations. J Clin Psychol 2006 Apr;62(4):459-480. [doi: 10.1002/jclp.20243] [Medline: 16470714]
40. de Mello MF, de Jesus Mari J, Bacaltchuk J, Verdeli H, Neugebauer R. A systematic review of research findings on the efficacy of interpersonal therapy for depressive disorders. Eur Arch Psychiatry Clin Neurosci 2005 Apr;255(2):75-82. [doi: 10.1007/s00406-004-0542-x] [Medline: 15812600]
41. Vøllestad J, Nielsen MB, Nielsen GH. Mindfulness- and acceptance-based interventions for anxiety disorders: A systematic review and meta-analysis. Br J Clin Psychol 2012 Sep;51(3):239-260. [doi: 10.1111/j.2044-8260.2011.02024.x] [Medline: 22803933]
42. A-Tjak JGL, Davis ML, Morina N, Powers MB, Smits JAJ, Emmelkamp PMG. A meta-analysis of the efficacy of acceptance and commitment therapy for clinically relevant mental and physical health problems. Psychother Psychosom 2015;84(1):30-36. [doi: 10.1159/000365764] [Medline: 25547522]
43. Shea BJ, Reeves BC, Wells G, Thuku M, Hamel C, Moran J, et al. AMSTAR 2: A critical appraisal tool for systematic reviews that include randomised or non-randomised studies of healthcare interventions, or both. BMJ 2017 Sep 21;358:j4008 [FREE Full text] [doi: 10.1136/bmj.j4008] [Medline: 28935701]
44. Moher D, Liberati A, Tetzlaff J, Altman DG, PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Med 2009 Jul 21;6(7):e1000097 [FREE Full text] [doi: 10.1371/journal.pmed.1000097] [Medline: 19621072]
45. Statista. New York, NY: Statista; 2019. Number of apps available in leading app stores as of 1st quarter 2019 URL: https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/ [accessed 2019-07-12]
46. Shen N, Levitan M, Johnson A, Bender JL, Hamilton-Page M, Jadad AAR, et al. Finding a depression app: A review and content analysis of the depression app marketplace. JMIR Mhealth Uhealth 2015 Feb 16;3(1):e16 [FREE Full text] [doi: 10.2196/mhealth.3713] [Medline: 25689790]
47. Christoforou M, Sáez Fonseca JA, Tsakanikos E. Two novel cognitive behavioral therapy-based mobile apps for agoraphobia: Randomized controlled trial. J Med Internet Res 2017 Nov 24;19(11):e398 [FREE Full text] [doi: 10.2196/jmir.7747] [Medline: 29175809]
48. Kinderman P, Hagan P, King S, Bowman J, Chahal J, Gan L, et al. The feasibility and effectiveness of Catch It, an innovative CBT smartphone app. BJPsych Open 2016 May;2(3):204-209 [FREE Full text] [doi: 10.1192/bjpo.bp.115.002436] [Medline: 27703777]
49. Kuhn E, Kanuri N, Hoffman JE, Garvert DW, Ruzek JI, Taylor CB. A randomized controlled trial of a smartphone app for posttraumatic stress disorder symptoms. J Consult Clin Psychol 2017 Mar;85(3):267-273. [doi: 10.1037/ccp0000163] [Medline: 28221061]
50. Bakker D, Kazantzis N, Rickwood D, Rickard N. A randomized controlled trial of three smartphone apps for enhancing public mental health. Behav Res Ther 2018 Oct;109:75-83. [doi: 10.1016/j.brat.2018.08.003] [Medline: 30125790]
51. Stiles-Shields C, Montague E, Kwasny MJ, Mohr DC. Behavioral and cognitive intervention strategies delivered via coached apps for depression: Pilot trial. Psychol Serv 2019 May;16(2):233-238 [FREE Full text] [doi: 10.1037/ser0000261] [Medline: 30407055]
52. Flett JAM, Hayne H, Riordan BC, Thompson LM, Conner TS. Mobile mindfulness meditation: A randomised controlled trial of the effect of two popular apps on mental health. Mindfulness 2019;10(5):863-876. [doi: 10.1007/s12671-018-1050-9]
53. Lee RA, Jung ME. Evaluation of an mHealth app (DeStressify) on university students' mental health: Pilot trial. JMIR Ment Health 2018 Jan 23;5(1):e2 [FREE Full text] [doi: 10.2196/mental.8324] [Medline: 29362209]
54. Roepke AM, Jaffee SR, Riffle OM, McGonigal J, Broome R, Maxwell B. Randomized controlled trial of SuperBetter, a smartphone-based/internet-based self-help tool to reduce depressive symptoms. Games Health J 2015 Jun;4(3):235-246. [doi: 10.1089/g4h.2014.0046] [Medline: 26182069]

55. Carey TA, Haviland J, Tai SJ, Vanags T, Mansell W. MindSurf: A pilot study to assess the usability and acceptability of a smartphone app designed to promote contentment, wellbeing, and goal achievement. BMC Psychiatry 2016 Dec 12;16(1):442 [FREE Full text] [doi: 10.1186/s12888-016-1168-z] [Medline: 27955643]
56. Thoma N, Pilecki B, McKay D. Contemporary cognitive behavior therapy: A review of theory, history, and evidence. Psychodyn Psychiatry 2015 Sep;43(3):423-461. [doi: 10.1521/pdps.2015.43.3.423] [Medline: 26301761]
57. Webb M, de Ybarra DR, Baker E, Reis I, Carey M. Cognitive-behavioral therapy to promote smoking cessation among African American smokers: A randomized clinical trial. J Consult Clin Psychol 2010 Feb;78(1):24-33. [doi: 10.1037/a0017669] [Medline: 20099947]
58. Magill M, Ray LA. Cognitive-behavioral treatment with adult alcohol and illicit drug users: A meta-analysis of randomized controlled trials. J Stud Alcohol Drugs 2009 Jul;70(4):516-527 [FREE Full text] [doi: 10.15288/jsad.2009.70.516] [Medline: 19515291]
59. Ehde DM, Dillworth TM, Turner JA. Cognitive-behavioral therapy for individuals with chronic pain: Efficacy, innovations, and directions for research. Am Psychol 2014;69(2):153-166. [doi: 10.1037/a0035747] [Medline: 24547801]
60. World Health Organization. Scalable Psychological Interventions for People in Communities Affected by Adversity: A New Area of Mental Health and Psychosocial Work at WHO. Geneva, Switzerland: World Health Organization; 2017. URL: https://apps.who.int/iris/bitstream/handle/10665/254581/WHO-MSD-MER-17.1-eng.pdf;jsessionid=3E3A6AD80F948549B0FD8C4BB4B14E5C?sequence [accessed 2020-06-05]
61. Dimidjian S, Arch JJ, Schneider RL, Desormeau P, Felder JN, Segal ZV. Considering meta-analysis, meaning, and metaphor: A systematic review and critical examination of "third wave" cognitive and behavioral therapies. Behav Ther 2016 Nov;47(6):886-905. [doi: 10.1016/j.beth.2016.07.002] [Medline: 27993339]
62. Marshall JM, Dunstan DA, Bartik W. Smartphone psychology: New approaches towards safe and efficacious mobile mental health apps. Prof Psychol Res Pr 2020 Jun;51(3):214-222 [FREE Full text] [doi: 10.1037/pro0000278]
63. Marshall JM, Dunstan DA, Bartik W. Clinical or gimmickal: The use and effectiveness of mobile mental health apps for treating anxiety and depression. Aust N Z J Psychiatry 2020 Jan;54(1):20-28 [FREE Full text] [doi: 10.1177/0004867419876700] [Medline: 31552747]
64. Alyami M, Giri B, Alyami H, Sundram F. Social anxiety apps: A systematic review and assessment of app descriptors across mobile store platforms. Evid Based Ment Health 2017 Aug;20(3):65-70. [doi: 10.1136/eb-2017-102664] [Medline: 28666986]
65. Bakker D, Kazantzis N, Rickwood D, Rickard N. Mental health smartphone apps: Review and evidence-based recommendations for future developments. JMIR Ment Health 2016 Mar 01;3(1):e7 [FREE Full text] [doi: 10.2196/mental.4984] [Medline: 26932350]
66. Orman J, O'Dea B. E-Therapy in primary care mental health. Aust J Gen Pract 2018 Apr;47(4):168-172 [FREE Full text] [doi: 10.31128/AJGP-11-17-4410] [Medline: 29621855]
67. Clough BA, Casey LM. Smart designs for smart technologies: Research challenges and emerging solutions for scientist-practitioners within e-mental health. Prof Psychol Res Pr 2015 Dec;46(6):429-436. [doi: 10.1037/pro0000053]
68. Broussard JD, Teng EJ. Models for enhancing the development of experiential learning approaches within mobile health technologies. Prof Psychol Res Pr 2019 Jun;50(3):195-203. [doi: 10.1037/pro0000234]
69. Jessen S, Mirkovic J, Ruland CM. Creating gameful design in mHealth: A participatory co-design approach. JMIR Mhealth Uhealth 2018 Dec 14;6(12):e11579 [FREE Full text] [doi: 10.2196/11579] [Medline: 30552080]

## Abbreviations

**ACT:** acceptance and commitment therapy
**AMSTAR:** A MeaSurement Tool to Assess systematic Reviews
**CBT:** cognitive behavioral therapy
**DBT:** dialectical behavior therapy
**IPT:** interpersonal therapy
**mHealth:** mobile health
**PASSR:** Protocol for App Store Systematic Reviews
**PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses
**RCT:** randomized controlled trial

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Original Paper

# Associations of Electronic Device Use Before and After Sleep With Psychological Distress Among Chinese Adults in Hong Kong: Cross-Sectional Study

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## Abstract

**Background:** Hong Kong has a high rate of electronic device (e-device; computer, smartphone, and tablet) use. However, little is known about the associations of the duration of e-device use before and after sleep with psychological symptoms.

**Objective:** This study aimed to investigate the associations of the duration of e-device use before and after sleep with psychological distress.

**Methods:** A probability-based telephone survey was conducted on 3162 Hong Kong adults (54.6% female; mean age 47.4 years, SD 18.3 years) in 2016. Multivariate linear and Poisson regressions were used to calculate adjusted regression coefficients (aBs) and prevalence ratios (aPRs) of anxiety and depressive symptoms (measured by Patient Health Questionnaire-4) for the duration from waking to the first e-device use (≥61, 31-60, 6-30, and ≤5 minutes) and the duration of e-device use before sleeping (≤5, 6-30, 31-60, and ≥61 minutes).

**Results:** The first e-device use in ≤5 (vs ≥61) minutes after waking was associated with anxiety (aB 0.35, 95% CI 0.24-0.46; aPR 1.74, 95% CI 1.34-2.25) and depressive symptoms (aB 0.27, 95% CI 0.18-0.37; aPR 1.84, 95% CI 1.33-2.54). Using e-devices for ≥61 (vs ≤5) minutes before sleeping was also associated with anxiety (aB 0.17, 95% CI 0.04-0.31; aPR 1.32, 95% CI 1.01-1.73) and depressive symptoms (aB 0.17, 95% CI 0.05-0.28; aPR 1.47, 95% CI 1.07-2.02). E-device use both ≤5 minutes after waking and for ≥61 minutes before sleeping was strongly associated with anxiety (aB 0.68, 95% CI 0.47-0.90; aPR 2.64, 95% CI 1.90-3.67) and depressive symptoms (aB 0.55, 95% CI 0.36-0.74; aPR 2.56, 95% CI 1.69-3.88).

**Conclusions:** E-device use immediately (≤5 minutes) after waking and use for a long duration (≥61 minutes) before sleeping were associated with anxiety and depressive symptoms among Chinese adults in Hong Kong.

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**KEYWORDS**

addictive behavior; anxiety; computers; depression; devices; internet; smartphone; withdrawal symptoms

## Introduction

Electronic devices (e-devices), such as computers, smartphones, and tablets, are forms of information and communication technology (ICT) that have become essential to modern society [1,2]. The penetration rate of e-devices in Hong Kong, one of the most modern cities in China, is among the highest globally (eg, 80.2% for computers and 88.6% for smartphones) [3,4].

Given their popularity, the excessive use of e-devices, particularly smartphones, has been increasingly reported [1,5-8].

Despite ongoing debates about how to best define excessive use within the domain of addiction, the World Health Organization (WHO) [1] reported that excessive e-device use is arguably a type of behavioral addiction that presents as a repetitive pattern of behavioral engagement in a specific area (ie, e-device use), which eventually affects behavioral engagement in other domains [5,6,9]. Gaming disorders, which are closely associated with e-device use, have recently been included in the WHO's 11th Revision of the International Classification of Diseases (ICD-11) [9].

Increasing concerns have emerged about the adverse psychological effects of behavioral addiction with e-devices [8,10-17]. A recent systematic review found that e-device addiction was associated with anxiety (β coefficients, .12-.23) and depression (β coefficients, .15-.48) [15]. These findings were supported by another recent study finding that behavioral addiction to the internet and smartphones resulted in the imbalance of gamma-aminobutyric acid levels in the brain, which has been implicated in the development of depression and anxiety [18].

The WHO has urged the consideration of e-device use duration when defining behavioral addiction with e-devices [1]. Many people start and end their days with e-devices owing to their ubiquity and convenience [19]. Borrowing the concept of adopting the duration of the first tobacco use after waking up in the morning to assess tobacco addiction [20], the duration of the first e-device use may indicate the level of e-device addiction. As negative sleep outcomes, such as shortened sleep duration and sleep onset latency, are associated with excessive bedside e-device use [8,21-23], it is hypothesized that a longer duration of e-device use before sleep (ie, longer screen time before sleep) may also be associated with excessive use and behavioral addiction.

Little is known about the associations of the duration of e-device use before and after sleep with psychological symptoms. Most existing studies have focused on identifying the associations between psychological symptoms and the addiction of e-devices or on developing assessment instruments for e-device addiction [8,10-17]. In addition, most studies have focused only on young age groups, despite the rapid adoption of e-devices among older age groups [24]. Therefore, we aimed to investigate the association of psychological distress with the duration of e-device use before and after sleep in Hong Kong adults.

# Methods

## Study Design

The Hong Kong Family and Health Information Trends Survey (FHInTS) is part of the FAMILY project (A Jockey Club Initiative for a Harmonious Society project). The project has conducted periodic surveys to study family and individual health in relation to the use of ICTs in Hong Kong since 2009. The current FHInTS was the fifth edition of the project, and it explored the areas of ICT use for family health, health communication, and information acquisition [25]. Probability-based telephone surveys of individuals from the general public aged 18 years or older, who had at least one e-device and spoke Cantonese (ie, sample selection criteria), were conducted from January to August 2016 by trained interviewers of the Public Opinion Programme at the University of Hong Kong, a local reputable survey agency.

A random sampling method with two phases was adopted for the survey. Hong Kong's residential telephone directories were used to extract telephone numbers. The last digit of the extracted numbers was converted by adding or subtracting 1 or 2 to make up unlisted numbers in the directories. The telephone numbers were randomly listed using computer software (ie, first phase random sampling). In the second phase, the nearest birthday rule was used to randomly select a respondent [26]. To minimize selection bias by including individuals who work away from home during the day, the telephone survey was mostly conducted in the evenings. Verbal informed consent was collected from each participant over the telephone, and each telephone survey lasted for about 20 minutes. Ethical approval was obtained from the Institutional Review Board of The University of Hong Kong/Hospital Authority Hong Kong West Cluster.

## Measurements

Respondents were asked two questions to obtain the following data that were considered as duration indicators of e-device use: (1) duration from waking to the first e-device use (how long after getting up in the morning do you usually start using your computer, tablet, or smartphone? [response options were ≥61, 31-60, 6-30, and ≤5 minutes]) and (2) duration of e-device use before sleeping (how much time do you spend on using your computer, tablet, or smartphone before sleeping? [response options were ≤5, 6-30, 31-60, and ≥61 minutes]). Duration-related questions have been asked in other e-device addiction studies [13].

Anxiety and depressive symptoms were measured using Patient Health Questionnaire-4 (PHQ-4) [27], a brief self-reported instrument combining Generalized Anxiety Disorder-2 (GAD-2) [28] and Patient Health Questionnaire-2 (PHQ-2) [29] for screening anxiety and depression. GAD-2 and PHQ-2 scores of 3 or above on a scale of 0 to 6 were considered to indicate high risks of anxiety and depression [27]. The Cronbach α of PHQ-4 was .82, and the values of the PHQ-2 and GAD-2 subscales in this study were .71 and .75, respectively, which were considered satisfactory given their brevity. The score of PHQ-4 correlated well with the score of Perceived Stress Scale-4 [30] in a random subsample of 792 participants ($r$=0.61, $P$<.001), supporting its convergent validity.

## Statistical Analysis

All data were weighted by age, sex, and education level distributions according to the Hong Kong census data from 2015 [31]. The mean scores of anxiety and depressive symptoms related to sociodemographic characteristics, including sex, age, education level, and household income, and the duration from waking to the first e-device use as well as the duration of e-device use before sleeping were compared using the independent sample $t$ test or one-way analysis of variance (ANOVA), as appropriate. The Spearman rank correlation coefficient was calculated to analyze the correlation between the duration from waking to the first e-device use and the duration of e-device use before sleeping. A linear regression was used to compute adjusted regression coefficients (aBs) of anxiety and depressive symptoms for the duration from waking to the first e-device use and the duration of e-device use before sleeping. Age, sex, highest education level, and monthly household income were included in the adjusted regression models. Similar to the linear regression, Poisson regression with a robust variance estimator [32] was used to calculate the adjusted prevalence ratios (aPRs) of risk for anxiety and depression in terms of different durations of e-device use after waking and before sleeping, adjusting for age, sex, education level, and household income. As subgroup analyses, we included multiplicative interaction terms of the participants' durations of e-device use with each demographic in the regression models to compute *P* values for interaction effects. A sensitivity test was performed by repeating multivariate linear regression models using the PHQ-4 score as the outcome variable. Available case analysis was used to handle missing data, as the proportion of missing data was very low. Stata version 15 (StataCorp) was used for all analyses, and a *P* value <.05 was regarded as statistically significant.

## Results

### Participant Characteristics

Among 6890 adults eligible for the FHInTS, who were contacted, 5080 successfully completed the interviews (response rate 73.73%). Of these 5080 respondents, 3162 (62.24%) possessed at least one e-device and were included in the present study. The mean age of the respondents was 47.40 years (SD 18.32). Additionally, 54.55% (weighted 1833/3361) were female, 79.77% (2681/3361) were aged 25 to 64 years, 85.66% (2879/3361) had secondary or higher education, and 68.42% (2058/3008) had a monthly household income of HK $20,000 (US $2564; US $1=HK $7.80) or more (Table 1).

**Table 1.** Weighted mean scores of anxiety and depressive symptoms by sociodemographic characteristics in Hong Kong adults who used e-devices.

| Characteristic | Value (N=3162), n (%[a]) | Weighted value (N=3361), n (%[a]) | Anxiety symptoms (GAD-2[b] score; (mean 1.10, SD 0.02) | | Depressive symptoms (PHQ-2[c] score; mean 0.72, SD 0.02) | |
|---|---|---|---|---|---|---|
| | | | Score | *P* value[d] | Score | *P* value[d] |
| **Sex** | | | | .01 | | .76 |
| Male | 1226 (38.77) | 1528 (45.45) | 1.04 | | 0.75 | |
| Female | 1936 (61.23) | 1833 (54.55) | 1.13 | | 0.71 | |
| **Age (years)** | | | | <.001 | | <.001 |
| 18-24 | 527 (16.67) | 382 (11.36) | 1.67 | | 1.25 | |
| 25-34 | 325 (10.28) | 695 (20.68) | 1.50 | | 1.04 | |
| 35-44 | 393 (12.43) | 701 (20.87) | 1.23 | | 0.80 | |
| 45-54 | 599 (18.94) | 725 (21.56) | 1.03 | | 0.61 | |
| 55-64 | 715 (22.61) | 560 (16.66) | 0.81 | | 0.49 | |
| ≥65 | 603 (19.07) | 298 (8.88) | 0.69 | | 0.42 | |
| **Education** | | | | <.001 | | .11 |
| Primary or less | 387 (12.24) | 482 (14.34) | 0.79 | | 0.54 | |
| Secondary | 1452 (45.92) | 1766 (52.55) | 1.00 | | 0.70 | |
| Tertiary or greater | 1323 (41.84) | 1113 (33.11) | 1.29 | | 0.79 | |
| **Monthly household income[e] (HK $)** | | | | .13 | | .01 |
| ≤19,999 | 961 (34.07) | 950 (31.58) | 1.11 | | 0.77 | |
| 20,000-39,999 | 928 (32.90) | 1065 (35.40) | 1.08 | | 0.74 | |
| ≥40,000 | 932 (33.04) | 993 (33.02) | 1.09 | | 0.64 | |
| **Duration from waking to the first e-device use (four categories)** | | | | <.001 | | <.001 |
| ≥61 min | 1418 (45.02) | 1409 (42.21) | 0.92 | | 0.58 | |
| 31-60 min | 389 (12.35) | 452 (13.53) | 1.06 | | 0.77 | |
| 6-30 min | 628 (19.94) | 684 (20.49) | 1.09 | | 0.74 | |
| ≤5 min | 715 (22.70) | 793 (23.77) | 1.47 | | 0.98 | |
| **Duration from waking to the first e-device use (two categories)** | | | | <.001 | | <.001 |
| ≥6 min | 2435 (77.30) | 2544 (76.23) | 0.99 | | 0.65 | |
| ≤5 min | 715 (22.70) | 793 (23.77) | 1.47 | | 0.98 | |
| **Duration of e-device use before sleeping (four categories)** | | | | <.001 | | <.001 |
| ≤5 min | 1117 (35.51) | 1009 (30.26) | 0.82 | | 0.50 | |
| 6-30 min | 1033 (32.84) | 1162 (34.85) | 1.16 | | 0.74 | |
| 31-60 min | 559 (17.77) | 661 (19.81) | 1.27 | | 0.93 | |
| ≥61 min | 437 (13.89) | 503 (15.08) | 1.43 | | 0.98 | |
| **Duration of e-device use before sleeping (two categories)** | | | | <.001 | | <.001 |
| ≤60 min | 2709 (86.11) | 2832 (84.92) | 1.04 | | 0.68 | |
| ≥61 min | 437 (13.89) | 503 (15.08) | 1.43 | | 0.98 | |
| **Combined duration[f]** | | | | <.001 | | <.001 |
| ≥6W[g] & ≤60S[h] | 2144 (68.37) | 2206 (66.46) | 0.95 | | 0.62 | |
| ≥6W[g] & ≥61S[h] | 281 (8.96) | 325 (9.78) | 1.24 | | 0.86 | |
| ≤5W[g] & ≤60S[h] | 555 (17.70) | 610 (18.39) | 1.40 | | 0.92 | |
| ≤5W[g] & ≥61S[h] | 156 (4.97) | 178 (5.37) | 1.76 | | 1.19 | |

[a] Calculated percentages were rounded off to two decimal places, accordingly combined percentages can exceed 100%.

[b] GAD-2: Generalized Anxiety Disorder Questionnaire-2.

[c] PHQ-2: Patient Health Questionnaire-2.

[d] *P* for *t* test (two groups) or ANOVA (three groups or above).

[e] US $1=HK $7.8.

[f] Duration from waking to the first e-device use plus duration of e-device use before sleeping (two categorizations).

[g] 6W and 5W denote the duration from waking to the first e-device use for 6 minutes and 5 minutes, respectively.

[h] 60S and 61S denote the duration of e-device use before sleeping for 60 minutes and 61 minutes, respectively.

### Associations of Participant Characteristics With Psychological Distress

Anxiety symptoms were associated with being female (*P*=.01), being younger (*P*<.001), and having higher education levels (*P*<.001), whereas depressive symptoms were associated with being younger (*P*<.001) and having lower income (*P*=.01) (Table 1). Respondents who first used e-devices for shorter durations of time after waking had more anxiety and depressive symptoms (*P*<.001). Similarly, respondents who used e-devices for longer periods of time before sleeping had more anxiety and depressive symptoms (*P*<.001). Respondents who first used e-devices within shorter periods of time after waking and for longer periods of time before sleeping had more anxiety and depressive symptoms as compared with other e-device use patterns (*P*<.001).

### Associations of E-Device Use Before and After Sleep With Psychological Distress

The duration of e-device use before sleeping was significantly correlated with the duration from waking to the first e-device use ($r_s$=0.304, *P*<.001). Shorter periods of time between waking and e-device use (ie, ≤5 minutes) were associated with both anxiety (aB 0.35, 95% CI 0.24-0.46) and depressive symptoms (aB 0.27, 95% CI 0.18-0.37) (Tables 2 and 3). Shorter durations of time before e-device use were consistently associated with both anxiety (aPR 1.74, 95% CI 1.34-2.25) and depressive symptoms (aPR 1.84, 95% CI 1.33-2.54) (Tables 4 and 5). Longer durations of e-device use before sleeping (ie, ≥61 minutes) were associated with higher risks of both anxiety (aB 0.17, 95% CI 0.04-0.31; aPR 1.32, 95% CI 1.01-1.73) and depressive symptoms (aB 0.17, 95% CI 0.05-0.28; aPR 1.47, 95% CI 1.07-2.02). The use of e-devices starting ≤5 minutes after waking and for ≥61 minutes before sleeping showed the strongest association with anxiety and depressive symptoms (aB 0.68 and aPR 2.64 for anxiety symptoms; aB 0.55 and aPR 2.56 for depressive symptoms). The results from the sensitivity test, which examined the association of e-device use before and after sleep with PHQ-4 scores, yielded similar results, thus supporting the robustness of the findings.

**Table 2.** Linear regression of anxiety symptoms for the duration from waking to the first e-device use and duration of e-device use before sleeping.

| Duration assessed and time (min)[a] | Anxiety symptoms (GAD-2[b] score) | | | |
|---|---|---|---|---|
| | Crude regression coefficient (95% CI) | *P* | Adjusted[c] regression coefficient (95% CI) | *P* |
| **Duration from waking to the first e-device use** | | | | |
| ≥61 | 0 | | 0 | |
| 31-60 | 0.03 (−0.11 to 0.17) | .69 | −0.10 (−0.25 to 0.04) | .17 |
| 6-30 | 0.07 (−0.05 to 0.20) | .24 | −0.09 (−0.22 to 0.04) | .18 |
| ≤5 | 0.45 (0.34 to 0.57) | <.001 | 0.31 (0.18 to 0.43) | <.001 |
| Trend | | <.001 | | <.001 |
| ≥6 | 0 | | 0 | |
| ≤5 | 0.43 (0.32 to 0.54) | <.001 | 0.35 (0.24 to 0.46) | <.001 |
| **Duration of e-device use before sleeping** | | | | |
| ≤5 | 0 | | 0 | |
| 6-30 | 0.26 (0.15 to 0.38) | <.001 | 0.04 (−0.09 to 0.16) | .54 |
| 31-60 | 0.41 (0.27 to 0.54) | <.001 | 0.16 (0.01 to 0.31) | .03 |
| ≥61 | 0.54 (0.40 to 0.68) | <.001 | 0.23 (0.07 to 0.39) | .004 |
| Trend | | <.001 | | .002 |
| ≤60 | 0 | | 0 | |
| ≥61 | 0.34 (0.21 to 0.47) | <.001 | 0.17 (0.04 to 0.31) | .01 |
| **Duration from waking to the first e-device use plus duration of e-device use before sleeping (two categorizations)** | | | | |
| ≥6W[d] & ≤60S[e] | 0 | | 0 | |
| ≥6W[d] & ≥61S[e] | 0.19 (0.04 to 0.35) | .02 | −0.01 (−0.18 to 0.15) | .87 |
| ≤5W[d] & ≤60S[e] | 0.35 (0.23 to 0.47) | <.001 | 0.26 (0.13 to 0.38) | <.001 |
| ≤5W[d] & ≥61S[e] | 0.82 (0.61 to 1.03) | <.001 | 0.68 (0.47 to 0.90) | <.001 |
| Trend | | <.001 | | <.001 |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] GAD-2: Generalized Anxiety Disorder Questionnaire-2.

[c] Adjusted for age, sex, highest education level, and monthly household income.

[d] 6W and 5W denote the duration from waking to the first e-device use for 6 minutes and 5 minutes, respectively.

[e] 60S and 61S denote the duration of e-device use before sleeping for 60 minutes and 61 minutes, respectively.

**Table 3.** Linear regression of depressive symptoms for the duration from waking to the first e-device use and duration of e-device use before sleeping.

| Duration assessed and time (min)[a] | Depressive symptoms (PHQ-2[b] score) | | | |
|---|---|---|---|---|
| | Crude regression coefficient (95% CI) | *P* | Adjusted[c] regression coefficient (95% CI) | *P* |
| **Duration from waking to the first e-device use** | | | | |
| ≥61 | 0 | | 0 | |
| 31-60 | 0.11 (−0.02 to 0.24) | .09 | 0.04 (−0.09 to 0.17) | .52 |
| 6-30 | 0.09 (−0.02 to 0.20) | .09 | −0.01 (−0.12 to 0.11) | .92 |
| ≤5 | 0.40 (0.30 to 0.50) | <.001 | 0.28 (0.17 to 0.39) | <.001 |
| Trend | | <.001 | | <.001 |
| ≥6 | 0 | | 0 | |
| ≤5 | 0.36 (0.26 to 0.45) | <.001 | 0.27 (0.18 to 0.37) | <.001 |
| **Duration of e-device use before sleeping** | | | | |
| ≤5 | 0 | | 0 | |
| 6-30 | 0.16 (0.06 to 0.26) | .001 | 0.01 (−0.10 to 0.13) | .79 |
| 31-60 | 0.41 (0.29 to 0.52) | <.001 | 0.19 (0.06 to 0.32) | .005 |
| ≥61 | 0.44 (0.31 to 0.57) | <.001 | 0.22 (0.08 to 0.37) | .002 |
| Trend | | <.001 | | <.001 |
| ≤60 | 0 | | 0 | |
| ≥61 | 0.28 (0.16 to 0.39) | <.001 | 0.17 (0.05 to 0.28) | .006 |
| **Duration from waking to the first e-device use plus duration of e-device use before sleeping (two categorizations)** | | | | |
| ≥6W[d] & ≤60S[e] | 0 | | 0 | |
| ≥6W[d] & ≥61S[e] | 0.16 (0.02 to 0.30) | .02 | 0.03 (−0.11 to 0.18) | .67 |
| ≤5W[d] & ≤60S[e] | 0.30 (0.19 to 0.41) | <.001 | 0.20 (0.09 to 0.31) | <.001 |
| ≤5W[d] & ≥61S[e] | 0.67 (0.49 to 0.85) | <.001 | 0.55 (0.36 to 0.74) | <.001 |
| Trend | | <.001 | | <.001 |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] PHQ-2: Patient Health Questionnaire-2.

[c] Adjusted for age, sex, highest education level, and monthly household income.

[d] 6W and 5W denote the duration from waking to the first e-device use for 6 minutes and 5 minutes, respectively.

[e] 60S and 61S denote the duration of e-device use before sleeping for 60 minutes and 61 minutes, respectively.

**Table 4.** Poisson regression of anxiety symptoms for the duration from waking to the first e-device use and duration of e-device use before sleeping.

| Duration assessed and time (min)[a] | Value, n (%) | Anxiety symptoms (GAD-2[b] score ≥3)[c] | | | |
|---|---|---|---|---|---|
| | | Crude prevalence ratio (95% CI) | *P* | Adjusted[d] prevalence ratio (95% CI) | *P* |
| **Duration from waking to the first e-device use** | | | | | |
| ≥61 | 139 (9.88) | 1 | | 1 | |
| 31-60 | 44 (9.84) | 1.00 (0.66-1.50) | .98 | 0.81 (0.52-1.27) | .36 |
| 6-30 | 60 (8.75) | 0.89 (0.62-1.26) | .50 | 0.71 (0.48-1.04) | .08 |
| ≤5 | 135 (16.99) | 1.72 (1.30-2.27) | <.001 | 1.51 (1.12-2.04) | .007 |
| Trend | | | .002 | | .04 |
| ≥6 | 218 (9.59) | 1 | | 1 | |
| ≤5 | 135 (16.99) | 1.78 (1.39-2.27) | <.001 | 1.74 (1.34-2.25) | <.001 |
| **Duration of e-device use before sleeping** | | | | | |
| ≤5 | 90 (8.89) | 1 | | 1 | |
| 6-30 | 130 (11.23) | 1.26 (0.92-1.73) | .14 | 1.00 (0.70-1.42) | .99 |
| 31-60 | 76 (11.49) | 1.29 (0.91-1.83) | .15 | 0.98 (0.66-1.47) | .92 |
| ≥61 | 82 (16.22) | 1.82 (1.28-2.60) | .001 | 1.31 (0.88-1.97) | .18 |
| Trend | | | .002 | | .25 |
| ≤60 | 296 (10.46) | 1 | | 1 | |
| ≥61 | 82 (16.22) | 1.55 (1.16-2.08) | .003 | 1.32 (0.96-1.82) | .09 |
| **Duration from waking to the first e-device use plus duration of e-device use before sleeping (two categorizations)** | | | | | |
| ≥6W[e] & ≤60S[f] | 208 (9.45) | 1 | | 1 | |
| ≥6W[e] & ≥61S[f] | 31 (9.69) | 1.03 (0.65-1.62) | .91 | 0.74 (0.48-1.16) | .26 |
| ≤5W[e] & ≤60S[f] | 85 (13.87) | 1.47 (1.10-1.95) | .009 | 1.36 (1.03-1.79) | .047 |
| ≤5W[e] & ≥61S[f] | 50 (28.11) | 2.98 (2.10-4.22) | <.001 | 2.64 (1.90-3.67) | <.001 |
| Trend | | | <.001 | | <.001 |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] GAD-2: Generalized Anxiety Disorder Questionnaire-2.

[c] High prevalence of anxiety.

[d] Adjusted for age, sex, highest education level, and monthly household income.

[e] 6W and 5W denote the duration from waking to the first e-device use for 6 minutes and 5 minutes, respectively.

[f] 60S and 61S denote the duration of e-device use before sleeping for 60 minutes and 61 minutes, respectively.

**Table 5.** Poisson regression of depressive symptoms for the duration from waking to the first e-device use and duration of e-device use before sleeping.

| Duration assessed and time (min)[a] | Value, n (%) | Depressive symptom (PHQ-2[b] score ≥3)[c] | | | |
|---|---|---|---|---|---|
| | | Crude prevalence ratio (95% CI) | *P* | Adjusted[d] prevalence ratio (95% CI) | *P* |
| **Duration from waking to the first e-device use** | | | | | |
| ≥61 | 85 (6.04) | 1 | | 1 | |
| 31-60 | 24 (5.36) | 0.89 (0.53-1.49) | .65 | 0.80 (0.45-1.44) | .46 |
| 6-30 | 46 (6.72) | 1.11 (0.71-1.74) | .64 | 1.10 (0.68-1.79) | .69 |
| ≤5 | 98 (12.33) | 2.04 (1.43-2.92) | <.001 | 1.83 (1.23-2.72) | .003 |
| Trend | | | <.001 | | .005 |
| ≥6 | 137 (6.04) | 1 | | 1 | |
| ≤5 | 98 (12.33) | 2.02 (1.49-2.75) | <.001 | 1.84 (1.33-2.54) | <.001 |
| **Duration of e-device use before sleeping** | | | | | |
| ≤5 | 56 (5.53) | 1 | | 1 | |
| 6-30 | 69 (5.93) | 1.07 (0.70-1.65) | .75 | 0.77 (0.47-1.26) | .29 |
| 31-60 | 71 (10.69) | 1.93 (1.25-2.99) | .003 | 1.21 (0.73-2.03) | .46 |
| ≥61 | 54 (10.78) | 1.95 (1.23-3.10) | .005 | 1.40 (0.83-2.36) | .21 |
| Trend | | | <.001 | | .049 |
| ≤60 | 195 (6.90) | 1 | | 1 | |
| ≥61 | 54 (10.78) | 1.56 (1.08-2.26) | .02 | 1.47 (1.07-2.02) | .02 |
| **Duration from waking to the first e-device use plus duration of e-device use before sleeping (two categorizations)** | | | | | |
| ≥6W[e] & ≤60S[f] | 127 (5.78) | 1 | | 1 | |
| ≥6W[e] & ≥61S[f] | 24 (7.49) | 1.30 (0.77-2.17) | .32 | 1.18 (0.74-1.87) | .48 |
| ≤5W[e] & ≤60S[f] | 68 (11.13) | 1.93 (1.35-2.75) | <.001 | 1.66 (1.19-2.31) | .003 |
| ≤5W[e] & ≥61S[f] | 30 (16.78) | 2.91 (1.79-4.73) | <.001 | 2.56 (1.69-3.88) | <.001 |
| Trend | | | <.001 | | <.001 |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] PHQ-2: Patient Health Questionnaire-2.

[c] High prevalence of depression.

[d] Adjusted for sex, age, highest education level, and monthly household income.

[e] 6W and 5W denote the duration from waking to the first e-device use for 6 minutes and 5 minutes, respectively.

[f] 60S and 61S denote the duration of e-device use before sleeping for 60 minutes and 61 minutes, respectively.

## Interaction Effect Between Demographics and E-Device Use for Psychological Distress

Subgroup analyses showed that the associations of e-device use before and after sleep with psychological distress differed according to the participants' demographics. Participants who were female, were aged 18 to 44 years, received secondary education or below, or had household income of HK $39,999 or less showed stronger associations in all but two outcomes; participants who received tertiary education and used e-devices starting ≤5 minutes after waking showed stronger associations with anxiety symptoms, whereas the association between female participants who used e-devices for ≥61 minutes before sleeping and depressive symptoms was not relevant (Tables 6 and 7).

**Table 6.** Interaction effect between Hong Kong adults’ demographics and e-device use for anxiety symptoms.

| Characteristic[a] | Duration from waking to the first e-device use (≥6 min vs ≤5 min) | | | Duration of e-device use before sleeping (≤60 min vs ≥61 min) | | |
|---|---|---|---|---|---|---|
| | n | Coefficient[b] | *P* [c] | n | Coefficient[b] | *P* [c] |
| **Sex** | | | <.001 | | | .002 |
| Men | 1370 | 0.18 (0.02 to 0.34) | | 1365 | 0.10 (−0.07 to 0.28) | |
| Women | 1629 | 0.47 (0.31 to 0.62) | | 1628 | 0.23 (0.03 to 0.44) | |
| **Age (years)[d,e]** | | | <.001 | | | <.001 |
| 18-44 | 1574 | 0.47 (0.32 to 0.62) | | 1572 | 0.26 (0.09 to 0.44) | |
| ≥45 | 1425 | 0.23 (0.06 to 0.39) | | 1422 | 0.07 (−0.14 to 0.28) | |
| **Education[d,f]** | | | <.001 | | | <.001 |
| Secondary or less | 1984 | 0.28 (0.14 to 0.43) | | 1983 | 0.25 (0.07 to 0.42) | |
| Tertiary or more | 1015 | 0.45 (0.27 to 0.62) | | 1011 | 0.08 (−0.12 to 0.29) | |
| **Income (HK$)[d,g,h]** | | | <.001 | | | <.001 |
| ≤39,999 | 2006 | 0.45 (0.30 to 0.59) | | 2009 | 0.24 (0.07 to 0.42) | |
| ≥40,000 | 993 | 0.21 (0.04 to 0.38) | | 985 | 0.06 (−0.14 to 0.27) | |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] Regression coefficient (95% CI) adjusted for age, sex, highest education level, and monthly household income.

[c] *P* value for interaction.

[d] Demographic variables were summarized into binary groups.

[e] The median age of the participants was 47 years.

[f] 66.9% and 33.1% of the Hong Kong population attained secondary education or below and tertiary education, respectively, in 2018.

[g] The median monthly household income of economically active households in Hong Kong was around HK $36,000 in 2019.

[h] Monthly household income (US $1=HK $7.8).

**Table 7.** Interaction effect between Hong Kong adults’ demographics and e-device use for depressive symptoms.

| Characteristic[a] | Duration from waking to the first e-device use (≥6 min vs ≤5 min) | | | Duration of e-device use before sleeping (≤60 min vs ≥61 min) | | |
|---|---|---|---|---|---|---|
| | n | Coefficient[b] | *P* [c] | n | Coefficient[b] | *P* [c] |
| **Sex** | | | .004 | | | .07 |
| Men | 1371 | 0.21 (0.07 to 0.36) | | 1366 | 0.06 (−0.01 to 0.22) | |
| Women | 1629 | 0.31 (0.17 to 0.44) | | 1629 | 0.04 (−0.00 to 0.07) | |
| **Age (years)**[d,e] | | | <.001 | | | <.001 |
| 18-44 | 1574 | 0.36 (0.22 to 0.51) | | 1572 | 0.27 (0.11 to 0.44) | |
| ≥45 | 1426 | 0.19 (0.06 to 0.32) | | 1423 | 0.03 (−0.14 to 0.20) | |
| **Education**[d,f] | | | <.001 | | | .03 |
| Secondary or less | 1984 | 0.28 (0.15 to 0.41) | | 1984 | 0.20 (0.05 to 0.36) | |
| Tertiary or more | 1015 | 0.27 (0.12 to 0.43) | | 1011 | 0.11 (−0.07 to 0.29) | |
| **Income (HK $)**[d,g,h] | | | <.001 | | | <.001 |
| ≤39,999 | 2007 | 0.42 (0.29 to 0.55) | | 2010 | 0.26 (0.11 to 0.42) | |
| ≥40,000 | 993 | 0.03 (−0.12 to 0.17) | | 985 | 0.00 (−0.18 to 0.18) | |

[a] All data were weighted by sex, age, and education level distribution of the Hong Kong general population.

[b] Regression coefficient (95% CI) adjusted for age, sex, highest education level, and monthly household income.

[c] *P* value for interaction.

[d] Demographic variables were summarized into binary groups.

[e] The median age of the participants was 47 years.

[f] 66.9% and 33.1% of the Hong Kong population attained secondary education or below and tertiary education, respectively, in 2018.

[g] The median monthly household income of economically active households in Hong Kong was around HK $36,000 in 2019.

[h] Monthly household income (US $1=HK $7.8).

## Discussion

### Principal Findings

With a large population-representative sample of adult e-device users in Hong Kong, we found that both shorter time to the first e-device use and longer duration of e-device use before sleeping were associated with anxiety and depressive symptoms. The associations tended to be stronger in females, those aged 18 to 44 years, those who received secondary education or below, and those who had household income of HK $39,999 or less. To our knowledge, no study has yet presented the associations reported herein. Additionally, this research provides findings of Chinese adults’ e-device use in response to the dearth of e-device research in adult populations, particularly those of Chinese ethnicity.

### Comparison With Prior Work

While many studies [8,33-37] have consistently reported that e-device addiction or excessive e-device use is associated with anxiety and depressive symptoms, our study demonstrated that the use of an e-device for more than 60 minutes before sleeping increased the risk of depression and anxiety. Studies have established that excessive e-device use before sleeping (ie, ≥61 min) can affect sleep quality. It has been found that the emission of electromagnetic radiation from e-devices impairs the circadian rhythm, and the blue light emitted by e-devices affects melatonin secretion [38-40]. Particularly, one study found that the use of e-devices for over 60 minutes in the evening greatly hindered melatonin secretion at night (mean 48%, SD 4%) [40], resulting in poor sleep quality and quantity. Similarly, Hysing et al [22] asserted that using e-devices in the last hour (ie, 60 minutes) before sleeping prolonged sleep onset latency and increased sleep deficiency. Sleep quality [41-43] and melatonin secretion [44-46] are both negatively associated with anxiety and depressive symptoms. Therefore, it can be deduced that poor sleep quantity and quality owing to reduced melatonin secretion from over 60 minutes of e-device use before sleeping, in addition to prolonged exposure to its electromagnetic radiation, can potentially lead to psychological distress. The overall evidence so far suggests that e-devices should not be used for more than 60 minutes before bedtime, and whether such a practice can enhance sleep quality should be investigated.

A high number of public surveys [19,47-49] reported on the pattern of the first e-device use soon after waking as a symptom of the excessive use of e-devices, using descriptive data for the duration. For example, a global survey reported that 33% of people in developed countries, ranging from 20% in France to 64% in South Korea, used smartphones within 5 minutes of waking [47]. In this study, 22.7% (715/3162) of participants used an e-device within 5 minutes of waking, which is similar to the rate reported in France. Haug et al [13] identified that the duration from waking to the first e-device use was a strong indicator of e-device addiction. In addition to the association between e-device use in the morning and e-device addiction, our study showed that the duration from waking to the first e-device use was inversely associated with psychological symptoms.

We identified that there was a strong correlation between the duration from waking to the first e-device use and the duration of e-device use before sleeping. We also identified that the combination of e-device use ≤5 minutes after waking and ≥61 minutes before sleeping showed the highest risk and very high risk for anxiety and depressive symptoms, respectively, as compared with other combinations of e-device use duration. E-device use (particularly with the internet) at bedtime could affect e-device use in the morning. The behavior to immediately use e-devices upon waking is seen as a withdrawal symptom caused by excessive e-device use at bedtime [37,50,51]. In other words, late e-device use at bedtime would cause the first thought on one's mind to use the device again upon waking up as a withdrawal symptom. Lin et al [50] also stressed that a prominent withdrawal behavior of e-device addiction is the pattern of e-device use upon waking (ie, an "eye opener"). The pattern would be a release of the craving to be continuously stimulated by real-time interactions via the e-device (or the internet) immediately upon opening one's eyes in the morning. The "eye opener" concept has also been used to describe withdrawal symptoms of substance use (eg, alcohol and tobacco) in the literature [20,52].

We found that the association between the duration of e-device use and psychological distress differed according to participants' demographics. Although it would be difficult to directly compare our study with existing studies as our findings are novel, some studies have reported that problematic e-device use has been more commonly found among female individuals [13,53-55], younger individuals [13,56,57], those with low education levels [56,57], and those with low household income [56,58,59], which is consistent with our findings. However, the associations were inconsistent in some other studies. For example, de-Sola et al [57] reported that being male had a higher correlation with problematic e-device use than being female, whereas Kim et al [60] found no sex and household income differences. Long et al [12] found that household income was positively associated with problematic e-device use. Hence, a meta-analysis will be useful to affirm the associations of the duration of e-device use and psychological distress with different demographic groups in populations. A qualitative study will also be required to obtain an in-depth understanding of these associations within the Hong Kong context.

Although excessive e-device use is associated with negative health effects, including psychological symptoms, avoiding the use of e-devices cannot be recommended as they are integrated into the daily life of humans in this era owing to their benefits (eg, enhanced communication [61]). Nurturing healthy patterns of device use should be advised. Given that a large number of respondents used e-devices upon waking and before sleeping, public education should be provided for the association between excessive "bedside" e-device use and negative psychological symptoms. Seo et al [18] also identified that a psychosocial intervention could rectify the chemical imbalances in the brain and reduce the negative psychological distress caused by the excessive use of e-devices. Health care professionals can also consider using brief duration indicators to screen for psychological distress among individuals in clinical and community settings.

## Limitations

Our study had several limitations. First, this study only included the e-devices of computers, smartphones, and tablets, and thus, it omitted the use of other e-devices, such as televisions and video game consoles, although most of the content would have involved computers or smartphones. Second, we conducted a probability-based telephone survey. The lack of mobile phone survey data may cause sampling bias. Third, the type of e-device used and the type of online activities conducted on e-devices may affect the durations of e-device use before and after sleep and associated psychological distress. Additional studies would be useful to assess these associations. Fourth, the causal relationships between respondents' use of e-devices and psychological symptoms (eg, psychological distress induces excessive use and vice versa [15]) were uncertain owing to the cross-sectional study design [62]. Fifth, the respondents only included adults; no young people under 18 years old were included. Given that exposure to e-devices begins early in life and that young people rapidly adopt e-devices, the inclusion of young people in future studies would provide a better understanding of the associations between the pattern of e-device use and acute and chronic mental health problems. Finally, all data were self-reported, which might be subject to recall bias and social desirability bias. Future studies should consider including objective data on e-device use and adverse health effects.

## Conclusions

We provided the first findings of the associations of a shorter duration to the first e-device use after waking and a longer duration of e-device use before sleeping with high risks of anxiety and depressive symptoms in adults. Although further studies are required to examine causal relations, these two simple measures could help identify and manage e-device users with high risks for anxiety and depression.

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## Conflicts of Interest

None declared.

## References

1. World Health Organization. Public health implications of excessive use of the internet, computers, smartphones and similar electronic devices: meeting report. Geneva: World Health Organization; 2015 Presented at: World Health Organization Meeting; August 27-29, 2014; Main Meeting Hall, Foundation for Promotion of Cancer Research, National Cancer Research Centre, Tokyo, Japan URL: http://apps.who.int/iris/handle/10665/184264
2. The World Bank. Washington, DC: The World Bank; 2016. World Development Report 2016: Digital Dividends URL: http://www.worldbank.org/en/publication/wdr2016 [accessed 2018-07-02]
3. Census and Statistics Department. 2017. Thematic Household Survey Report No. 62: Information technology usage and penetration URL: https://www.statistics.gov.hk/pub/B11302622017XXXXB0100.pdf [accessed 2018-12-23]
4. Pew Research Center. 2016. Smartphone ownership and Internet usage continues to climb in emerging economies URL: http://www.pewglobal.org/2016/02/22/smartphone-ownership-and-internet-usage-continues-to-climb-in-emerging-economies/ [accessed 2018-02-23]
5. Kwon M, Kim D, Cho H, Yang S. The smartphone addiction scale: development and validation of a short version for adolescents. PLoS One 2013;8(12):e83558 [FREE Full text] [doi: 10.1371/journal.pone.0083558] [Medline: 24391787]
6. Mok JY, Choi SW, Kim D, Choi J, Lee J, Ahn H, et al. Latent class analysis on internet and smartphone addiction in college students. Neuropsychiatr Dis Treat 2014;10:817-828 [FREE Full text] [doi: 10.2147/NDT.S59293] [Medline: 24899806]
7. Choi S, Kim D, Choi J, Ahn H, Choi E, Song W, et al. Comparison of risk and protective factors associated with smartphone addiction and Internet addiction. J Behav Addict 2015 Dec;4(4):308-314 [FREE Full text] [doi: 10.1556/2006.4.2015.043] [Medline: 26690626]
8. Demirci K, Akgönül M, Akpinar A. Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. J Behav Addict 2015 Jun;4(2):85-92 [FREE Full text] [doi: 10.1556/2006.4.2015.010] [Medline: 26132913]
9. World Health Organization. 2019. Gaming disorder URL: https://www.who.int/features/qa/gaming-disorder/en/ [accessed 2019-07-10]
10. Cho H, Kim DJ, Park JW. Stress and adult smartphone addiction: Mediation by self-control, neuroticism, and extraversion. Stress Health 2017 Dec;33(5):624-630. [doi: 10.1002/smi.2749] [Medline: 28332778]
11. Dalbudak E, Evren C, Aldemir S, Coskun KS, Ugurlu H, Yildirim FG. Relationship of internet addiction severity with depression, anxiety, and alexithymia, temperament and character in university students. Cyberpsychol Behav Soc Netw 2013 Apr;16(4):272-278. [doi: 10.1089/cyber.2012.0390] [Medline: 23363230]
12. Long J, Liu T, Liao Y, Qi C, He H, Chen S, et al. Prevalence and correlates of problematic smartphone use in a large random sample of Chinese undergraduates. BMC Psychiatry 2016 Nov 17;16(1):408 [FREE Full text] [doi: 10.1186/s12888-016-1083-3] [Medline: 27855666]
13. Haug S, Castro RP, Kwon M, Filler A, Kowatsch T, Schaub MP. Smartphone use and smartphone addiction among young people in Switzerland. J Behav Addict 2015 Dec;4(4):299-307 [FREE Full text] [doi: 10.1556/2006.4.2015.037] [Medline: 26690625]
14. Lemola S, Perkinson-Gloor N, Brand S, Dewald-Kaufmann JF, Grob A. Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. J Youth Adolesc 2015 Mar;44(2):405-418. [doi: 10.1007/s10964-014-0176-x] [Medline: 25204836]
15. Elhai JD, Dvorak RD, Levine JC, Hall BJ. Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. J Affect Disord 2017 Jan 01;207:251-259. [doi: 10.1016/j.jad.2016.08.030] [Medline: 27736736]
16. Enez Darcin A, Noyan C, Nurmedov S, Yilmaz O, Dilbaz N. Smartphone Addiction in Relation with Social Anxiety and Loneliness Among University Students in Turkey. European Psychiatry 2015 Mar;30(1):505. [doi: 10.1016/s0924-9338(15)30398-9]
17. Kim J, Seo M, David P. Alleviating depression only to become problematic mobile phone users: Can face-to-face communication be the antidote? Computers in Human Behavior 2015 Oct;51:440-447. [doi: 10.1016/j.chb.2015.05.030]
18. Seo H, Jeong E, Choi S, Kwon Y, Park H. Neurotransmitters in young people with Internet and smartphone addiction: A comparision with normal controls and changes after cognitive behavioral therapy. : Radiological Society of North America; 2017 Presented at: The Radiological Society of North America's 103rd Scientific Assembly and Annual Meeting (RSNA 2017); November 26-December 1, 2017; Chicago, USA URL: https://press.rsna.org/timssnet/media/pressreleases/14_pr_target.cfm?ID=1997
19. IDC. 2013. Always connected: How smartphonessocial keep us engaged URL: https://www.nu.nl/files/IDC-Facebook%20Always%20Connected%20%281%29.pdf [accessed 2018-09-27]
20. Transdisciplinary Tobacco Use Research Center (TTURC) Tobacco Dependence, Baker TB, Piper ME, McCarthy DE, Bolt DM, Smith SS, et al. Time to first cigarette in the morning as an index of ability to quit smoking: implications for nicotine dependence. Nicotine Tob Res 2007 Nov;9 Suppl 4:S555-S570 [FREE Full text] [doi: 10.1080/14622200701673480] [Medline: 18067032]
21. Hale L, Guan S. Screen time and sleep among school-aged children and adolescents: a systematic literature review. Sleep Med Rev 2015 Jun;21:50-58 [FREE Full text] [doi: 10.1016/j.smrv.2014.07.007] [Medline: 25193149]

22. Hysing M, Pallesen S, Stormark KM, Jakobsen R, Lundervold AJ, Sivertsen B. Sleep and use of electronic devices in adolescence: results from a large population-based study. BMJ Open 2015 Mar 02;5(1):e006748 [FREE Full text] [doi: 10.1136/bmjopen-2014-006748] [Medline: 25643702]
23. Carter B, Rees P, Hale L, Bhattacharjee D, Paradkar MS. Association Between Portable Screen-Based Media Device Access or Use and Sleep Outcomes: A Systematic Review and Meta-analysis. JAMA Pediatr 2016 Dec 01;170(12):1202-1208 [FREE Full text] [doi: 10.1001/jamapediatrics.2016.2341] [Medline: 27802500]
24. Census and Statistics Department. 2018. Thematic Household Survey Report No. 64: Pattern of smoking & Personal computer and Internet penetration URL: http://www.statistics.gov.hk/pub/B11302642018XXXXB0100.pdf [accessed 2019-07-01]
25. Shen C, Wang MP, Chu JT, Wan A, Viswanath K, Chan SS, et al. Health App Possession Among Smartphone or Tablet Owners in Hong Kong: Population-Based Survey. JMIR Mhealth Uhealth 2017 Jun 05;5(6):e77 [FREE Full text] [doi: 10.2196/mhealth.7628] [Medline: 28583905]
26. Ziersch AM, Baum FE. Involvement in civil society groups: Is it good for your health? J Epidemiol Community Health 2004 Jun;58(6):493-500 [FREE Full text] [doi: 10.1136/jech.2003.009084] [Medline: 15143118]
27. Löwe B, Wahl I, Rose M, Spitzer C, Glaesmer H, Wingenfeld K, et al. A 4-item measure of depression and anxiety: validation and standardization of the Patient Health Questionnaire-4 (PHQ-4) in the general population. J Affect Disord 2010 Apr;122(1-2):86-95. [doi: 10.1016/j.jad.2009.06.019] [Medline: 19616305]
28. Kroenke K, Spitzer RL, Williams JB, Monahan PO, Löwe B. Anxiety disorders in primary care: prevalence, impairment, comorbidity, and detection. Ann Intern Med 2007 Mar 06;146(5):317-325. [doi: 10.7326/0003-4819-146-5-200703060-00004] [Medline: 17339617]
29. Löwe B, Kroenke K, Gräfe K. Detecting and monitoring depression with a two-item questionnaire (PHQ-2). J Psychosom Res 2005 Mar;58(2):163-171. [doi: 10.1016/j.jpsychores.2004.09.006] [Medline: 15820844]
30. Leung DY, Lam T, Chan SS. Three versions of Perceived Stress Scale: validation in a sample of Chinese cardiac patients who smoke. BMC Public Health 2010 Aug 25;10:513 [FREE Full text] [doi: 10.1186/1471-2458-10-513] [Medline: 20735860]
31. Census and Statistics Department. 2015. Hong Kong Population Projections 2015-2064 URL: https://www.statistics.gov.hk/pub/B1120015062015XXXXB0100.pdf [accessed 2019-07-11]
32. Barros AJ, Hirakata VN. Alternatives for logistic regression in cross-sectional studies: an empirical comparison of models that directly estimate the prevalence ratio. BMC Med Res Methodol 2003 Oct 20;3:21 [FREE Full text] [doi: 10.1186/1471-2288-3-21] [Medline: 14567763]
33. Harwood J, Dooley JJ, Scott AJ, Joiner R. Constantly connected – The effects of smart-devices on mental health. Computers in Human Behavior 2014 May;34:267-272. [doi: 10.1016/j.chb.2014.02.006]
34. Hong F, Chiu S, Huang D. A model of the relationship between psychological characteristics, mobile phone addiction and use of mobile phones by Taiwanese university female students. Computers in Human Behavior 2012 Nov;28(6):2152-2159. [doi: 10.1016/j.chb.2012.06.020]
35. Elhai JD, Tiamiyu M, Weeks J. Depression and social anxiety in relation to problematic smartphone use. Internet Research 2018 Apr 04;28(2):315-332. [doi: 10.1108/intr-01-2017-0019]
36. Hwang K, Yoo Y, Cho O. Smartphone Overuse and Upper Extremity Pain, Anxiety, Depression, and Interpersonal Relationships among College Students. The Journal of the Korea Contents Association 2012 Oct 28;12(10):365-375. [doi: 10.5392/jkca.2012.12.10.365]
37. Matar Boumosleh J, Jaalouk D. Depression, anxiety, and smartphone addiction in university students- A cross sectional study. PLoS One 2017;12(8):e0182239 [FREE Full text] [doi: 10.1371/journal.pone.0182239] [Medline: 28777828]
38. Lee Y, Low B. Sleep pattern among electronic device users and its relationship with users' practice in Malaysia university community. Sleep Biol. Rhythms 2016 Feb 8;14(3):271-277. [doi: 10.1007/s41105-016-0052-z]
39. Cain N, Gradisar M. Electronic media use and sleep in school-aged children and adolescents: A review. Sleep Med 2010 Sep;11(8):735-742. [doi: 10.1016/j.sleep.2010.02.006] [Medline: 20673649]
40. Wood B, Rea MS, Plitnick B, Figueiro MG. Light level and duration of exposure determine the impact of self-luminous tablets on melatonin suppression. Appl Ergon 2013 Mar;44(2):237-240. [doi: 10.1016/j.apergo.2012.07.008] [Medline: 22850476]
41. Alvaro P, Roberts R, Harris JK. A Systematic Review Assessing Bidirectionality between Sleep Disturbances, Anxiety, and Depression. Sleep 2013 Jul 01;36(7):1059-1068 [FREE Full text] [doi: 10.5665/sleep.2810] [Medline: 23814343]
42. Augner C. Associations of Subjective Sleep Quality with Depression Score, Anxiety, Physical Symptoms and Sleep Onset Latency in Young Students. Cent Eur J Public Health 2011 Jun 1;19(2):115-117. [doi: 10.21101/cejph.a3647]
43. De-Sola Gutiérrez J, Rodríguez de Fonseca F, Rubio G. Cell-Phone Addiction: A Review. Front Psychiatry 2016;7:175 [FREE Full text] [doi: 10.3389/fpsyt.2016.00175] [Medline: 27822187]
44. Sundberg I, Ramklint M, Stridsberg M, Papadopoulos FC, Ekselius L, Cunningham JL. Salivary Melatonin in Relation to Depressive Symptom Severity in Young Adults. PLoS One 2016 Apr 4;11(4):e0152814 [FREE Full text] [doi: 10.1371/journal.pone.0152814] [Medline: 27042858]

45. Hansen MV, Andersen LT, Madsen MT, Hageman I, Rasmussen LS, Bokmand S, et al. Effect of melatonin on depressive symptoms and anxiety in patients undergoing breast cancer surgery: a randomized, double-blind, placebo-controlled trial. Breast Cancer Res Treat 2014 Jun;145(3):683-695. [doi: 10.1007/s10549-014-2962-2] [Medline: 24756186]
46. Hansen M, Halladin N, Rosenberg J, Gögenur I, Møller AM. Melatonin for pre- and postoperative anxiety in adults. Cochrane Database Syst Rev 2015 Apr 09(4):CD009861 [FREE Full text] [doi: 10.1002/14651858.CD009861.pub2] [Medline: 25856551]
47. Deloitte. 2017. Global mobile consumer trends, 2nd edition: Mobile continues its global reach into all aspects of consumers' lives URL: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Technology-Media-Telecommunications/gx-global-mobile-consumer-survey-2nd-edition.pdf [accessed 2018-05-16]
48. Lookout. 2012. Mobile mindset study URL: https://www.tecnostress.it/wp-content/uploads/2012/12/lookout-mobile-mindset-2012.pdf [accessed 2017-05-05]
49. Montag C, Kannen C, Lachmann B, Sariyska R, Duke É, Reuter M, et al. The importance of analogue zeitgebers to reduce digital addictive tendencies in the 21st century. Addict Behav Rep 2015 Dec;2:23-27 [FREE Full text] [doi: 10.1016/j.abrep.2015.04.002] [Medline: 29531991]
50. Lin Y, Chang L, Lee Y, Tseng H, Kuo TB, Chen S. Development and validation of the Smartphone Addiction Inventory (SPAI). PLoS One 2014;9(6):e98312 [FREE Full text] [doi: 10.1371/journal.pone.0098312] [Medline: 24896252]
51. Lin Y, Lin S, Yang C, Kuo T. Psychopathology of everyday life in the 21st century: smartphone addiction. In: Montag C, Reuter M, editors. Internet addiction: Neuroscientific approaches and therapeutical implications including smartphone addiction. Switzerland: Springer; 2017:339-358.
52. Bush B, Shaw S, Cleary P, Delbanco TL, Aronson MD. Screening for alcohol abuse using the cage questionnaire. The American Journal of Medicine 1987 Feb;82(2):231-235. [doi: 10.1016/0002-9343(87)90061-1]
53. Billieux J, Van der Linden M, Rochat L. The role of impulsivity in actual and problematic use of the mobile phone. Appl. Cognit. Psychol 2008 Dec;22(9):1195-1210. [doi: 10.1002/acp.1429]
54. Yang S, Lin C, Huang Y, Chang J. Gender differences in the association of smartphone use with the vitality and mental health of adolescent students. J Am Coll Health 2018 Oct;66(7):693-701. [doi: 10.1080/07448481.2018.1454930] [Medline: 29565784]
55. Chen B, Liu F, Ding S, Ying X, Wang L, Wen Y. Gender differences in factors associated with smartphone addiction: a cross-sectional study among medical college students. BMC Psychiatry 2017 Oct 10;17(1):341 [FREE Full text] [doi: 10.1186/s12888-017-1503-z] [Medline: 29017482]
56. Alhassan AA, Alqadhib EM, Taha NW, Alahmari RA, Salam M, Almutairi AF. The relationship between addiction to smartphone usage and depression among adults: a cross sectional study. BMC Psychiatry 2018 May 25;18(1):148 [FREE Full text] [doi: 10.1186/s12888-018-1745-4] [Medline: 29801442]
57. de-Sola J, Talledo H, Rodríguez de Fonseca F, Rubio G. Prevalence of problematic cell phone use in an adult population in Spain as assessed by the Mobile Phone Problem Use Scale (MPPUS). PLoS One 2017;12(8):e0181184 [FREE Full text] [doi: 10.1371/journal.pone.0181184] [Medline: 28771626]
58. Sahin S, Ozdemir K, Unsal A, Temiz N. Evaluation of mobile phone addiction level and sleep quality in university students. Pak J Med Sci 2013 Jul;29(4):913-918 [FREE Full text] [doi: 10.12669/pjms.294.3686] [Medline: 24353658]
59. Aljomaa SS, Al.Qudah MF, Albursan IS, Bakhiet SF, Abduljabbar AS. Smartphone addiction among university students in the light of some variables. Computers in Human Behavior 2016 Aug;61:155-164. [doi: 10.1016/j.chb.2016.03.041]
60. Kim H, Min J, Min K, Lee T, Yoo S. Relationship among family environment, self-control, friendship quality, and adolescents' smartphone addiction in South Korea: Findings from nationwide data. PLoS One 2018;13(2):e0190896 [FREE Full text] [doi: 10.1371/journal.pone.0190896] [Medline: 29401496]
61. Wang MP, Chu JT, Viswanath K, Wan A, Lam TH, Chan SS. Using Information and Communication Technologies for Family Communication and Its Association With Family Well-Being in Hong Kong: FAMILY Project. J Med Internet Res 2015 Aug 24;17(8):e207 [FREE Full text] [doi: 10.2196/jmir.4722] [Medline: 26303434]
62. Carlson MD, Morrison RS. Study design, precision, and validity in observational studies. J Palliat Med 2009 Jan;12(1):77-82 [FREE Full text] [doi: 10.1089/jpm.2008.9690] [Medline: 19284267]

## Abbreviations

**ANOVA:** analysis of variance
**FHInTS:** Family and Health Information Trends Survey
**GAD-2:** Generalized Anxiety Disorder-2
**ICT:** information and communication technology
**PHQ-2:** Patient Health Questionnaire-2
**PHQ-4:** Patient Health Questionnaire-4
**PR:** prevalence ratio
**WHO:** World Health Organization

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Original Paper

# Examining the Self-Harm and Suicide Contagion Effects of the Blue Whale Challenge on YouTube and Twitter: Qualitative Study

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## Abstract

**Background:** Research suggests that direct exposure to suicidal behaviors and acts of self-harm through social media may increase suicidality through imitation and modeling, particularly in more vulnerable populations. One example of a social media phenomenon that demonstrates how self-harming behavior could potentially be propagated is the blue whale challenge. In this challenge, adolescents and young adults are encouraged to engage in self-harm and eventually kill themselves.

**Objective:** This paper aimed to investigate the way individuals portray the blue whale challenge on social media, with an emphasis on factors that could pose a risk to vulnerable populations.

**Methods:** We first used a thematic analysis approach to code 60 publicly posted YouTube videos, 1112 comments on those videos, and 150 Twitter posts that explicitly referenced the blue whale challenge. We then deductively coded the YouTube videos based on the Suicide Prevention Resource Center (SPRC) safe messaging guidelines as a metric for the contagion risk associated with each video.

**Results:** The thematic analysis revealed that social media users post about the blue whale challenge to raise awareness and discourage participation, express sorrow for the participants, criticize the participants, or describe a relevant experience. The deductive coding of the YouTube videos showed that most of the videos violated at least 50% of the SPRC safe and effective messaging guidelines.

**Conclusions:** These posts might have the problematic effect of normalizing the blue whale challenge through repeated exposure, modeling, and reinforcement of self-harming and suicidal behaviors, especially among vulnerable populations such as adolescents. More effort is needed to educate social media users and content generators on safe messaging guidelines and factors that encourage versus discourage contagion effects.

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**KEYWORDS**

suicide; suicidal ideation; self-mutilation; mental health; self-injurious behavior; behavioral symptoms

## Introduction

### Background

Adolescents and young adults are the largest population using the internet as it has become essential for their schoolwork, information collection, and socializing [1-6]. Communication tools on the internet, including emails, direct texting, and blogging, have become fundamental in adolescents' social development [7-9]. More recently, web-based social networks, also known as social media, such as Facebook, Instagram, Twitter, and YouTube, have become increasingly popular and common among adolescents as sites where they can develop public accounts or profiles to connect with other individuals and see their list of connections and posts [7,9-11].

Although social media has created a number of opportunities for individuals to garner social support on the web [1,2,12-14], it also has the potential to negatively impact vulnerable individuals. Recent studies have highlighted how social media can be used to harass, discriminate [15,16], dox [17], and socially disenfranchise individuals [18-20]. Some research even suggests that social media use may be a contributing factor to the significant increase in suicide rates and depressive symptoms among adolescents in the past decade [1,21,22]. Evidence suggests that suicidal behavior can be propagated through social contagion effects, which occur when self-harming behavior is modeled, normalized, and reinforced in media depictions [23-25].

The public health and psychological literature has established that nonsuicidal self-injury (NSSI), or the purposeful infliction of damage to one's body through cutting, burning, or bruising, can be propagated through social modeling or imitating the behaviors of those we observe [23,26]. Similarly, direct exposure to suicidal behaviors through peers and/or media leads to an increase in suicidality through imitation and modeling [27,28]. These effects are referred to as suicide contagion and are most notable in adolescents and young adults [26,29,30]. There is a strong relationship between stories of suicide in traditional media and a subsequent increase in suicide rates [31,32], especially for prominent stories [33]. Vulnerable adolescents with preexisting mental health conditions and suicide risk factors are at a higher risk to perceive maladaptive self-injurious behavior as an effective coping strategy [34], particularly when they see others use these behaviors to achieve an attractive goal such as garnering the attention of others [35].

Depictions of suicide and self-harm in traditional media have been shown to have harmful effects on vulnerable individuals, even when they describe a false or fictional behavior [33,36]. Through social contagion, these harmful behaviors may occur more frequently because of the repetitive exposure and modeling via social media, especially when such content goes *viral* [23-25]. Virality is defined as "achieving a large number of views in a short time period" [37]. Such widespread exposure to harmful or suggestive content is particularly detrimental to vulnerable individuals, including adolescents and young adults [35,38]. As a result of research indicating contagion effects related to medial portrayals of suicide and self-harm behavior, the Suicide Prevention Resource Center (SPRC) developed a list of safe and effective messaging guidelines to advise media outlets on the means for reducing the contagion risks and harmful effects associated with media portrayals of suicidal behavior [39]. However, these guidelines are not consistently applied across media outlets, and they have not been specifically tailored for messaging via social media.

In the social media literature, Facebook's controversial *emotional contagion* study provides large-scale empirical evidence that indirect interactions via social media can also unknowingly influence one's emotional state [40-42]. For instance, researchers interviewed 90 inpatient adolescents with a history of NSSI, finding that most of the participants were exposed to NSSI via traditional or social media before engaging in self-harming behaviors [24]. Recent attention has focused on how social media, in particular, may play a role in mental health [43] and suicide risk [44,45]. Social media may influence suicidality via factors such as cyberbullying, peer pressure in forums to engage in self-injurious behavior, and glamorized graphic videos and images depicting lethal means used in such behavior [46,47]. In addition, exposure to certain methods of self-injury was directly related to engaging in this behavior, and the more frequently youth were exposed to self-injury–related content in the media, the more frequently they engaged in self-injurious activities [24]. However, exposure to self-injury alone does not relate to engagement in this behavior; rather, it is the frequency of the exposure to self-injury as a coping mechanism that can result in engagement [24]. The necessity for studying this contagion effect in the era of social media is that it can be spread and propagated through web-based social networks more rapidly and widely than through traditional media [48]. Such widespread exposure to harmful or suggestive content is particularly detrimental to vulnerable populations, including adolescents and young adults [35,37]. Thus, suicide contagion is the theoretical framework that motivates this study.

Most of the literature regarding adolescent web safety focuses on sexual or aggressive behaviors that put youth at risk [49]. Unfortunately, few studies have examined how social media can influence adolescents and young adults to engage in self-harming behavior [24,46,50]. Therefore, interdisciplinary research is beginning to highlight the urgent need to form a cohesive research agenda around digital self-harm [50], web-based NSSI [51], the use of social media to discuss deliberate self-harm acts [52,53], and acts of cybersuicide [52,53]. Most of this work, however, is in its early stages, with few drawing upon the developmental aspect of vulnerable adolescents' social media use.

### Objective

One example of viral self-harming behavior that has generated significant media attention is the blue whale challenge. Allegedly, in this challenge, adolescents and young adults are encouraged to engage in self-harm and eventually kill themselves. The media claims that this challenge, which was first released in Russia in 2013, includes a series of 50 challenges sent directly to teens, each with increasing levels of self-harm and isolation [54]. According to the media, the creator of the game, Philipp Budeikin, a Russian psychologist, wanted to "cleanse the society of biological waste," meaning the people who are willing to kill themselves for the game are *biological waste* [55]. Although there is insufficient evidence to support the existence of the challenge, we believe its portrayal on social media (or any similar medium) has the potential to impact vulnerable individuals. Research exploring ethical concerns related to the blue whale challenge, the effects the game may have on adolescents, and potential governmental interventions is needed. However, we are unaware of any research that examines potential suicide and NSSI contagion risk regarding the challenge. To address this gap in the literature, this study uses qualitative analysis research techniques to provide empirical evidence of the risk associated with self-harm and suicide contagion through the portrayal of the blue whale challenge on YouTube and Twitter posts. More specifically, the purpose of this study was to explore the following questions:

*Research question 1:* How is the blue whale challenge presented and described on YouTube and Twitter?

*Research question 2:* To what extent are YouTube videos compliant with the safe and effective suicide messaging guidelines provided by the SPRC?

## Methods

### Study Overview

In this study, we selected 2 social media platforms for data collection, YouTube and Twitter, as these are among the most popular social media platforms used by youth and young adults [56]. We identified the common themes of YouTube videos, comments on those videos, and Twitter posts by conducting a thematic analysis [57] on the data extracted from these platforms. The methodology we followed is an iterative qualitative coding process that starts by reviewing the raw data by multiple researchers and ends with a set of themes that represents the majority of the data [57]. In addition to the thematic analysis, we deductively coded the YouTube videos based on the SPRC safe and effective messaging guidelines to explore if these videos violated or adhered to these guidelines, the extent of violation, and which guidelines were violated more frequently than the others. To protect the identity of the users, we have not included any specific information regarding the user's names or their web identifier in the paper. In addition, the quotes included in the manuscript have been paraphrased without changing the meaning to make it challenging from a search-ability standpoint. Next, we describe in detail how we collected the data from social media platforms, how we conducted the thematic analysis, and how we coded the YouTube videos based on SPRC guidelines.

### Data Collection

YouTube and Twitter were selected as appropriate sources for data collection for 2 reasons. First, both platforms are ranked among the top 20 most popular social media sites. Second, posts on these platforms are normally open to the public [56,58,59]. The videos were searched using the YouTube search engine with the key phrase *blue whale challenge*. Next, we sorted the results by relevance, an option provided by YouTube that ranks the videos in descending order relative to the keyword queries based on several factors including "how well the title, description, and video content match the query and which videos have driven the most engagement for the query" [60]. Covington et al [61] described the algorithm used by YouTube in detail. We collected information from the first 60 videos on the list, which, combined, have a length of around 12 hours. The process of collecting and coding the data was iterative, an approach suggested by Saunders et al [62], to assure data saturation [63], which indicates that "on the basis of the data that have been collected or analyzed hitherto, further data collection and/or analysis are unnecessary" [62]. We did so by beginning the coding process with 40 videos and continued collecting videos until by the 60th video, wherein no more new codes in the data emerged. Interestingly, only 5 of these 60 videos required age verification. The following information was collected for each video: the link, the number of views, and the first 30 comments sorted by *top comments*, if present, as at this point, data saturation was achieved as found by iteratively collecting and coding data [63]. Top comments are identified by YouTube based on how many users like versus dislike a comment. A total of 1112 comments were collected for coding. Inclusion criteria for the videos were (1) relation to the blue whale challenge and (2) in English, translated into English, or contained English subtitles. Inclusion criteria for the comments were as follows: the comment (1) had to be in English and (2) include words. This data collection strategy was chosen to mimic the typical user behavior search strategy [64-66].

In addition to these YouTube videos, 150 Twitter posts were randomly collected using the social media monitoring and analytics tool Salesforce (Radian6) [66], which is a tool that listens, tracks, and analyzes conversations across different web-based channels based on the provided keywords [67]. Although Radian6 can only analyze posts in 10 different languages and is the most expensive social media monitoring tool, it can analyze almost all types of complex posts including forums/news/media, blogs, microblogs, geography, history, and sentiment [68]. These posts were collected from February 2012 to February 2018 using the keywords and inclusion criteria provided in Table 1. The timeline for collecting the data was chosen to cover the period where it is believed that blue whale challenge was most active [69]. We also conducted a Google Trends analysis with the key words *blue whale challenge* and found that the challenge was searched for most frequently from 2017 to 2018, which includes our search period. We initially collected 100 Twitter posts for analysis and continued to collect and code posts until no new codes emerged, meaning all posts collected reflected the existing codebook, with data saturation [62] occurring at 150 posts.

**Table 1.** Keywords, hashtags, and inclusion criteria for collecting Twitter posts using Radian6.

| Variable | Term or criteria |
|---|---|
| Keywords | • "Blue Whale Challenge"<br>• "Blue Whale Game"<br>• "BWC" |
| Hashtags | • "#BlueWhaleChallenge"<br>• "#BlueWhaleGame"<br>• "#Blue_Whale_Challenge"<br>• "#Blue_Whale_Game"<br>• "#BWC" |
| Inclusion criteria | • The post had to be in English and related to the blue whale challenge.<br>• No duplicates or "reTweets." |

### Thematic Analysis

We conducted a thematic analysis following the 6 phases recommended by Braun and Clarke [57]. First, the researchers familiarized themselves with the data (phase 1) and read and reread the data to note any initial observations. Then, the researchers started the coding process (phase 2) to identify the subthemes (codes) within the YouTube videos, YouTube comments, and Twitter posts. Due to the different policies, technical affordances, and data types of these platforms [50,58,59], we first analyzed each data type separately and then compared similar findings across platforms.

Initial codes were developed by dividing the top 40 videos, their top 30 related comments, and 100 Twitter posts between the 2 researchers. Each researcher then identified a set of codes on their own describing the data found in the videos, comments, and Twitter posts. The 2 researchers then had a meeting to combine their individual sets of codes into 3 comprehensive sets (1 for each type of data being analyzed). We called the resulting set of codes a codebook. The researchers conducted a pilot analysis on the top 40 YouTube videos, 695 YouTube comments under those videos, and 100 Twitter posts to ensure that the initial codebooks sufficiently summarized the data. Following the completion of the pilot analysis, the codebooks were modified by the both researchers together to more accurately summarize the data.

Once the codebooks were finalized, the full analysis of 60 YouTube videos, 1112 YouTube comments under those videos, and 150 Twitter posts was conducted. The 2 researchers separately coded all the data without collaboration to negate bias. Double-coding was allowed for the YouTube videos but not for the YouTube comments and Twitter posts. After coding was complete, they compared their codes with identify conflicts. When the 2 researchers disagreed, they used a consensus-forming process [70], where they discussed the underlying differences in their interpretation until they agreed which theme best suited the data. The final codebooks and results are provided in Multimedia Appendices 1-3. All coding results were entered into Atlas.ti [71], a qualitative coding software, to conduct axial coding and develop emergent themes across the 3 data types (phase 3). Both researchers worked together to tie the related codes into overarching themes. Then, the researchers reviewed the themes to ensure that they represented the data (phase 4). Following this, the researchers named, defined, and wrote about the themes (phases 5 and 6).

### Coding Based on Safe and Effective Messaging Guidelines

The SPRC developed 9 safe and effective messaging guidelines based on best practices from research to reduce the risk of inducing self-harm or suicide-related contagion in those who view a message (Table 2) [33,39,72]. Either following or violating these guidelines represents a metric for the contagion risk associated with a social media post. Each of the YouTube videos was compared with the 9 SPRC safe messaging guidelines by 2 researchers to determine if it adheres or violates each guideline. The researchers conducted 2 rounds of deductive coding [70] based on these guidelines. In the first round, they coded the first 40 YouTube videos individually. Then, they had a meeting to discuss any discrepancy in their coding strategy. Then, they started the second round of coding, where they coded all the 60 YouTube videos. The interrater reliability measured by Cohen κ was 0.66. If the 2 researchers disagreed on a code, the video was set aside for further consensus coding.

**Table 2.** Suicide Prevention Resource Center's safe and effective messaging for suicide prevention.

| Guideline | Description |
|---|---|
| Emphasize seeking help and provide information on where to find it | Provide steps for finding mental health treatment. Advise that help is available through local service providers and crisis centers and through the National Suicide Prevention Lifeline (1-800-273-8255). |
| Emphasize prevention | Highlight that suicide is avoidable and preventable and that there are actions for individuals who have suicidal thoughts to prevent them from acting on those thoughts [73]. |
| List the warning signs as well as the risk and protective factors of suicide | List the warning signs like the ones developed by the American Association of Suicidology. List what could both reduce and increase the risk of suicide; these can be found on pages 35-36 in the National Strategy for Suicide Prevention. Educate people on how to identify a person with self-harming thoughts. |
| Highlight effective treatments for underlying mental health problems | A total of 46% of people who died by suicide from 2014 to 2016 had a known mental health condition, with 67% of them having a history of treatment for substance abuse. Among them, 46.7% had recently been released from a psychiatric facility [74], a percentage which can be reduced by providing improved access to effective treatments and social support [75]. |
| Avoid glorifying or romanticizing suicide or people who died by suicide | Vulnerable younger adults may relate to the attention given to and sympathy for a person who committed suicide [76]. |
| Avoid normalizing suicide by presenting it as a common event | Suicide ideation is not seen as normal by most people, and they do not consider it an option. However, presenting suicide as a common event may remove this bias [77]. |
| Avoid presenting suicide as an inexplicable act or explain it as a result of stress only | Doing so may encourage identification with the victim as well as ignoring the complexity and preventability of suicide. Presenting suicide as explainable or a result of stress only misleads vulnerable individuals to believe that it is a normal response to common life situations [72,77-80]. |
| Avoid focusing on personal details of people who died by suicide | Vulnerable younger adults may feel they are like the person who committed suicide, eventually leading them to consider taking their lives in the same way [79]. |
| Avoid presenting overly detailed descriptions of suicide victims or methods of suicide | Including pictures and/or descriptions of where and how an individual died by suicide may lead a vulnerable person to imitate the act [79,80]. |

# Results

## Overview

This research focused on 2 main components: first, exploring the types of messages social media users share about the blue whale challenge via YouTube and Twitter, and second, the violation of SPRC guidelines in YouTube videos. We identified the common themes across YouTube videos, YouTube comments, and Twitter posts using an inductive coding approach. Then, we used a deductive coding approach to explore how many of the YouTube videos violated the SPRC guidelines. We subsequently compared these videos with the number of views and finally looked at which of the guidelines tended to be violated more often than others. In this section, we first present the 4 identified themes, and then, we describe the violation of the SPRC guidelines.

## Common Themes Across Social Media Platforms (Research Question 1)

We identified 4 common themes among all the posts in the 3 data types included in this study. Table 3 presents the themes, the corresponding codes (code definitions can be found in Multimedia Appendices 1-3), and the percentages of posts from each type of data. Below, we define each of the themes and provide examples from the extracted data. Note: We paraphrased illustrative verbatim quotes without changing the meaning for the following reasons: (1) to make it challenging to identify the users who made the post and (2) to fix any grammatical inaccuracy or typographical error that have been made by the user that wrote the post or comment.

**Table 3.** Common themes and corresponding codes among the 3 data types.

| Theme | Relevant codes from each codebook | YouTube videos, n (%) | YouTube comments, n (%) | Twitter posts, n (%) |
|---|---|---|---|---|
| Raising awareness about blue whale challenge and discouraging participation | • YouTube videos codebook (purpose of the videos—raise awareness; video topics—facts about the challenge; video topics—recommendations)<br>• YouTube comments codebook (criticizing the game; interventions and recommendations)<br>• Twitter codebook (awareness; information about the challenge) | 50 (83) | 315 (28.33) | 103 (68.7) |
| Expressing sorrow for people with mental health issues | • YouTube videos codebook (purpose of the videos—remembering the victims; Encouragement—negative)<br>• YouTube comments codebook (expressing sorrow; encouraging participants and parents)<br>• Twitter codebook (mental health) | 28 (47) | 123 (11.11) | 5 (3.3) |
| Criticizing or making jokes about the participants or the challenge | • YouTube videos codebook (purpose of the video—sarcastic, funny, or prank)<br>• YouTube comments codebook (criticizing the game; criticizing the victims; sarcastic, funny, or prank)<br>• Twitter codebook (sarcastic/funny/jokes) | 6 (10) | 530 (47.66) | 24 (16.0) |
| Providing experiences and asking to play | • YouTube videos codebook (video content—victims related)<br>• YouTube comments codebook (participating; personal experience)<br>• Twitter codebook (personal experience) | 36 (60) | 178 (16.01) | 1 (0.7) |

### *Theme 1: Raising Awareness About the Blue Whale Challenge and Discouraging Participation*

This theme included social media posts in which users were trying to raise awareness and warn parents about this dangerous phenomenon. YouTube videos in this context were either news reports or bloggers that started their videos by listing different names for the blue whale challenge and the statistics on how many people died by suicide due to this game. These videos, then, started discussing the tasks involved in the blue whale challenge, including that the only way out of the game is suicide. These videos frequently included clips from interviews with victims' parents or pictures of the victims while describing the blue whale challenge.

The YouTube comments in the awareness theme were against blue whale challenge and suggested that parents and authorities pay more attention to their children's safety. For example, 1 of the comments that falls in this category is:

> *This is getting ridiculous. The government, the Federal Bureau of Investigation, or someone needs to do something about it.*

The Twitter posts in this theme centered on awareness of this dangerous game. Users were trying to spread the word to make others aware of and read more about the challenge. One example of the Twitter posts in this theme is:

> *Please understand and beware of the Blue Whale Challenge. This is for the parents.*

This theme was most common in YouTube videos (approximately 83%) and Twitter posts (approximately 68.7%), suggesting that the majority of users on these 2 platforms are trying to spread the word about the danger of blue whale challenge.

### *Theme 2: Expressing Sorrow for People With Mental Health Issues*

This theme included social media posts in which the users expressed sorrow for those who participated in the blue whale challenge or people with mental illness issues. These videos primarily presented pictures of these people, accompanied by sad music. YouTube comments in the expressing sorrow theme included words of encouragement and support for people with mental health issues. An example of these supportive comments is:

> *Love you girl. So many people care about you. Depression is so horrible. Stay strong girl. We love you.*

The Twitter posts in the expressing sorrow theme primarily mentioned that people participate in the blue whale challenge because they have mental health issues, urge of self-harm, and suicidal ideation. One example of the Twitter posts reflecting this theme is:

> *The Blue Whale Challenge: Hey Mr. Scribe, Brush Up Your Archaic Knowledge of Mental Health.*

A high percentage of YouTube videos (approximately 47%) fell under this theme, but fewer YouTube comments (approximately 11.10%) and Twitter posts (approximately 3.3%) did.

### *Theme 3: Criticizing or Making Jokes About the Participants or the Challenge*

The third theme included social media posts from individuals who either criticized the individuals who participated in the blue whale challenge or made sarcastic comments about them or the challenge. The 6 YouTube videos that fell under this theme (10%) mentioned that adolescents participate in blue whale challenge just to “show off” and criticized them harshly or made sarcastic comments about them. The 511 YouTube comments in this theme (47.70%) criticized the blue whale challenge participants by saying things such as:

> *People who play this game are more stupid than the game itself. How can someone lose his sense and be manipulated by others like that. Grow up guys. You have brains to think and decide what is good and what is bad for you.*

The 24 Twitter posts in the criticizing theme (16.0%) were primarily sarcastic posts about the challenge itself rather than the people who participated in it. For example, 1 of these Twitter posts is:

> *Husband silently downloaded the Blue Whale Game on his wife's phone. Fifty days later the blue whale committed suicide.*

As seen in Table 3, this theme was mainly dominant in the YouTube comments, with a few YouTube videos and Twitter posts falling under this theme.

### *Theme 4: Providing Experiences and Asking to Play*

The last theme we identified included social media posts where users spoke in detail about someone who had participated or asked to play the game themselves. The providing experiences theme was very common in the YouTube videos (60%), where these 36 videos interviewed parents and provided pictures of the participants’ bodies showing instances of self-harm. This theme was slightly less common among the YouTube comments (16.00%), and these 178 comments were mainly about experiences of acquaintances or users who were asking to participate in the blue whale challenge. An example of the comments by someone asking to participate in blue whale challenge is:

> *I want to play the Blue Whale Game. Please give me the link.*

Only 2 Twitter posts fell in the providing experience theme (approximately 0.7%), which tended to be acquaintance stories. For example, 1 user posted the following on Twitter:

> *We just had a meeting here at work and this lady told us that her 10-year-old niece committed suicide because of this Blue Whale Challenge.*

A large number of YouTube videos fall under this theme, as opposed to the anecdotal YouTube comments and Twitter posts.

## Safe and Effective Messaging Guidelines (Research Question 2)

Of the 60 YouTube videos evaluated based on the SPRC safe messaging guidelines, 22 (37%) adhered to fewer than 3 of the 9 safe messaging guidelines, meaning that the videos were considered more unsafe than safe. Approximately 50% (30 videos) were considered neutral, meaning they adhered to only 4-6 of the guidelines, whereas the remaining 13% (8 videos) were considered more safe than unsafe because they adhered to 7 or more of the guidelines.

When compared with the number for views of each video, 50% (10 videos) of the top 20 viewed videos were more unsafe than safe, meaning that the videos violated at least 6 of the 9 criteria for safe and effective messaging about suicide. Only 10% (2 videos) of these 20 videos were considered more safe than unsafe, and 40% (8 videos) were considered neutral. The top 20 viewed videos had 46,099,923 views in total. Of the middle 20 most viewed videos, 30% (18 videos) were considered more unsafe than safe, 25% (15 videos) more safe than unsafe, and 45% (27 videos) neutral. The middle 20 viewed videos had 1,169,054 views in total. Of the 20 least viewed videos, 30% (18 videos) were considered more unsafe than safe, 5% (3 videos) more safe than unsafe, and 65% (39 videos) neutral. The 20 least viewed videos had only 123,450 views. All videos met at least one of the nine guidelines, and only 1 video met all 9 criteria. The total number of views for all 60 videos was 47,392,427, with the top 20 videos having 97.27% of the total views.

To better understand which guidelines were most frequently violated, we included the number of videos that violated each guideline in Table 4. The guidelines most frequently violated were “Highlight effective treatments for underlying mental health problems” and “Emphasize seeking help and provide information on where to find it.” As seen in Table 3, most YouTube videos were intended to raise awareness and warn parents and society about the blue whale challenge. It is expected and advisable for these types of videos to provide steps on how to treat such problems or information on where these details could be found, such as the National Suicide Prevention Lifeline [74]. However, as our results indicate, these videos failed to do so.

In addition, most of the videos violated the guidelines “Avoid presenting overly detailed descriptions of suicide victims or methods of suicide,” “Avoid glorifying or romanticizing suicide or people who died by suicide,” and “Avoid focusing on personal details of people who died by suicide.” These videos tended to include personal pictures of the victims, such as pictures of an arm with a whale carved on it. Most of the videos also mentioned that Philipp Budeikin, a 22-year-old dropout psychology student, is the curator of the challenge. They included pictures and quotes from the curator of the game, the most frequently occurring quote as:

> *The people who have died by the blue whale challenge are biological waste, and I was cleaning the society from them.*

A smaller but relatively high percentage of the videos included clips from interviews with the victims’ families and mock conversations between a victim and the curator showing how a person can participate in the challenge. Additionally, they mentioned that the challenge has other names, including but not limited to, *The Silent House*, *A Sea of Whales*, *Wake Me Up at 4:20 AM*, and *F57*. The majority of the videos described and provided details about the tasks and methods for attempting suicide in the challenge, including jumping off a high building, jumping in front of a train, and self-hanging. These videos also mentioned specific names of suicide cultures and web-based suicide groups or forums on social media that contributed to the spread of this challenge.

Approximately 67% (40 videos) of these videos violated the guideline “Avoid normalizing suicide by presenting it as a common event.” In these videos, general facts and statistics about the blue whale challenge, such as the number of suicides related to the challenge and the countries in which they occurred were provided. On the other hand, only a few videos provided support hotlines and recommendations to adolescents and parents about how to avoid this game.

**Table 4.** Percentage of videos violating each Suicide Prevention Resource Center safe messaging guideline.

| Guideline | Count, n (%) |
|---|---|
| Highlight effective treatments for underlying mental health problems | 54 (90) |
| Emphasize seeking help and provide information on where to find it | 47 (78) |
| Avoid presenting overly detailed descriptions of suicide victims or methods of suicide | 45 (75) |
| List the warning signs as well as the risk and protective factors of suicide | 43 (72) |
| Avoid normalizing suicide by presenting it as a common event | 40 (67) |
| Avoid glorifying or romanticizing suicide or people who died by suicide | 36 (55) |
| Emphasize prevention | 30 (50) |
| Avoid focusing on personal details of people who died by suicide | 30 (50) |
| Avoid presenting suicide as an inexplicable act or explain it as a result of stress only | 20 (33) |

## Discussion

### Overview

To the best of our knowledge, our study is the first to systematically document the quality, portrayal, and reach of the blue whale challenge on social media. In this study, we found that it is easy for adolescents to access almost any post about the blue whale challenge on social media, as only 5 of the YouTube videos blocked minors from viewing the content. We assessed the portrayal of the blue whale challenge on social media by investigating the common themes of the videos and posts and the videos’ adherence to the safe and effective messaging guidelines. We found that social media users post about blue whale challenge to raise awareness and discourage participation, to express sorrow for the participants, to criticize the participants, or to describe a relevant experience. Moreover, we found that the majority of the videos on YouTube violated at least 50% of the SPRC safe and effective messaging guidelines. In this section, we discuss in detail the themes found in the results and the potential consequences of the violated SPRC guidelines. We conclude this section by providing the design implications and recommendations to social media platforms and future directions for this research.

### Common Themes Across Social Media Platforms (Research Question 1)

The raising awareness theme was the most dominant theme and included posts that were meant to raise awareness and warn parents and society about the blue whale challenge. These posts were primarily anti-blue whale challenge, as opposed to pro-blue whale challenge. This finding implies that it is difficult to find information on how to participate in blue whale challenge or prosuicide information in comparison with obtaining antisuicide information on the internet, as found in a previous study [81]. It also implies that it is difficult to find videos from actual participants of the blue whale challenge. This finding could partially be due to the nature of the challenge in that it encourages participants to conduct self-harm secretly.

Another topic highlighted in blue whale challenge–related social media posts was that the users felt sorrow for people who participated in blue whale challenge or people with mental illness (theme expressing sorrow for people with mental health issues). This finding parallels our first 2 implications: it is not easy to find pro-blue whale challenge information on social media and even harder to find posts from actual participants. However, posts of this kind make the viewer think that there are a significant number of others participating in the blue whale challenge. This conclusion could lead them to believe that suicide and self-harm are normal responses to common life situations (eg, stress) rather than outcomes that can be prevented [39,76]. On the other hand, as seen in the criticizing theme, there were many posts in which people either criticized the adolescents who participated in the blue whale challenge or made fun of them, agreeing with the purpose of the blue whale challenge to clean “society of people with mental issues.” When people post critical comments about individuals with mental illness, they contribute to the stigma surrounding mental illness and discourage help-seeking behavior [82].

Finally, the providing experience theme showed that a large number of social media users tend to speak in detail about someone who participated in the blue whale challenge, providing their demographics or interviewing their parents or acquaintances who provide more details about the participant’s personal life. This theme was also found by other researchers who examined traditional media posts about suicide [76]. It is possible that reporting this level of detail might contribute to social modeling and contagion by leading vulnerable adolescents to feel that they are similar to the adolescents who participated in the blue whale challenge, making them more likely to participate or harm themselves [79].

### Safe and Effective Messaging Guidelines (Research Question 2)

We suggest that videos similar to those we examined could contribute to the spread of these risky challenges instead of meeting their intended purpose of raising awareness and decreasing participation. Most posts romanticized people who have died by following this challenge, and younger vulnerable individuals may see those victims as role models, possibly leading them to end their lives in the same way [76,81]. In violation of guidelines, the videos presented statistics about the number of suicides believed to be related to this challenge in a way that made suicide seem common [77]. In addition, the videos presented extensive personal information about the people who had died by suicide while playing the blue whale challenge. They also provided detailed descriptions of the final task, including pictures of self-harm and means of suicide, material that may encourage vulnerable adolescents to consider ending their lives and provide them with methods on how to do so [79,80]. On the other hand, these videos both failed to emphasize prevention by highlighting effective treatments for mental health problems and failed to encourage individuals with mental health problems to seek help as well as providing information on where to find it. For these reasons, we believe that these videos could contribute to the propagation of self-injury and suicidality through social modeling and imitation [23,26-28], which is known in the literature as the suicide contagion [29,30]. Suicide contagion is commonly promoted through traditional media [33,36], and we believe it is more likely to occur when social media is employed to depict self-harming behavior, as the content could easily go *viral* [23-25].

The SPRC safe and effective messaging guidelines are provided to help people working in suicide prevention, mental health promotion, or any other forms of media, which ensure that messages about suicide are safe, positive, and strategic [39]. Thus, these guidelines are applicable for assessing the appropriateness and safety of the content in messages in suicide campaigns and those discussing suicide across a variety of platforms [39,83]. Portrayals of both suicide and self-harm on social media platforms have the ability to increase that behavior in viewers regardless of their self-harm history, making the monitoring of self-harm and suicidal content crucial [84]. As adolescents often look for emotional support from the internet within a plethora of potentially harmful content, it is critical that web-based resources follow these guidelines, as not doing so may contribute to and/or increase the likelihood of someone with suicidal thoughts attempting suicide [39,77-80].

### Implications and Recommendations

Although there are no studies investigating how portrayals of the blue whale challenge can contribute to self-harm contagion, messages on social media may affect an individual's perception, belief, or behavior regarding self-harm. There are also no studies investigating similar challenges that are said to encourage self-harm and suicidal behavior, such as the momo challenge [85]. However, studies have clearly shown the harmful effects of newspapers, movies, and television portrayals that have led to increased rates of suicide and self-harm after violating safe messaging guidelines [33,86-90]. For example, Cooper et al [87] and Ayers et al [88] reported that suicide admission counts increased coinciding with the release of the Netflix series *13 Reasons Why*, which depicts suicide in a highly graphic and unsafe manner. Suicide contagion has been shown across a variety of entertainment and communication media, and social media has been the focus of recent research interest as a medium for contagion because of the ease with which harmful content can be spread [90-94].

As 2 of the most popular websites and social media platforms, YouTube and Twitter are potentially capable of influencing countless adolescents [2,56,59,66,95,96]. With most of the blue whale challenge-related posts on these platforms found to be potentially harmful to vulnerable populations, our findings suggest that it is urgent to monitor social media posts related to the challenge and similar self-harming challenges. The SPRC should appropriately inform social media users, particularly those with greater influence (eg, celebrities and news anchors) on how to address suicide or self-harm in a safe way to reduce contagion. This could be achieved using an algorithm that detects harmful content in the video before posting and provides recommendations to the user to edit or remove such content [97-100]. Although most YouTube users found the blue whale challenge to be a threat and forwarded a message as a means to warn others or speak out against it, they may unintentionally contribute to self-harm contagion. Therefore, it is critical for social media users to evaluate sources before creating and sharing information. They should also be educated on how to respond to unsafe posts and how to report such posts to social media administrators.

YouTube has the potential to become a powerful positive information dissemination platform with the contribution of mental health professionals and organizations [96,97]. Professionals and organizations can do so by actively participating on YouTube channels by creating and uploading videos that are safe, accurate, and trustworthy. Moreover, although only minimal barriers can realistically be applied to video uploads due to the nature of such platforms, there is a need to develop advanced algorithms and interfaces to highlight information that is safe, accurate, and trustworthy. In addition, integrating approved information available from federal agencies such as SPRC might increase the veracity and safety of information available. Greater effort is needed to educate the community about mental health and factors that could lead to self-harm, in addition to educating users on how to respond to unsafe posts. This could be accomplished by adding resources in suicide prevention campaigns or on social media platforms by providing a link on suicide-related videos to educate the public on how to identify and respond to unsafe videos. In addition, features such as crowdsourcing (obtaining information from internet users), asking users to report inaccurate and misleading information to prevent the spread of misinformation, could be integrated on social media sites.

## Limitations and Future Work

There are several limitations to our study, with many related to the data used. We only studied videos and posts about blue whale challenge that are publicly available. It is possible that more harmful videos could be posted on private pages or personal accounts. In addition, we only used hashtags that included blue whale challenge in them to collect the data. It is possible that there are unofficial hashtags that can be used by individuals at high risk of self-harm, allowing them to find related content without censorship. Additionally, the YouTube videos were selected according to their relevance to the topic based on 1 keyword. Ideally, videos should be randomly selected using several keywords and multiple hashtags. Moreover, our sample may differ from videos sampled at a subsequent time as YouTube is rapidly changing by nature. Furthermore, this study focused on 2 social media platforms, whereas people could be posting about the challenge on other platforms including, but not limited to, Facebook, VKontakte, Snapchat, and Instagram. Our study focused on 1 self-harm and suicide challenge, the blue whale challenge, although there are many other self-harm challenges such as the tide pod challenge and other suicide challenges such as the momo challenge.

Future research could include a comparison of the characteristics of posts about different challenges that exemplify various levels of self-harm to better understand the reasons for their viral spread. Understanding these factors will help build simulation models, such as agent-based models, to visualize the spread of these challenges. In addition, understanding these factors will help inform improved policies and interventions for eliminating the spread of harmful challenges among adolescents, such as those found by Luxton et al [47]. Integrating these policies into simulation models will help to identify the policies that are most effective in reducing these challenges with minimal cost.

## Conclusions

We investigated the characteristics of YouTube and Twitter posts focusing on the blue whale challenge and the characteristics of these posts that make them potentially harmful to vulnerable populations. Through our qualitative analysis, we found that although most videos and Twitter posts attempt to raise awareness about the challenge and inform parents, they may have unintentional harmful effects as most violated the SPRC safe messaging guidelines. We conclude that safe messaging guidelines should be more widely disseminated. Our data show that the majority of posters were not professionals and were likely to violate safe messaging guidelines. More efforts are needed to disseminate and educate the average person on messaging guidelines as well as factors that encourage contagion effects.

## Resources for Seeking Help

If you or a loved one has thoughts of suicide or self-harm, please contact the following resource: Suicide Prevention Hotline: 1-800-273-8255.

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## Conflicts of Interest

None declared.

Multimedia Appendix 1
Codebook for YouTube videos.
[PDF File (Adobe PDF File), 54 KB - mental_v7i6e15973_app1.pdf ]

Multimedia Appendix 2
Codebook for YouTube comments.
[PDF File (Adobe PDF File), 72 KB - mental_v7i6e15973_app2.pdf ]

Multimedia Appendix 3
Codebook for Twitter posts.
[PDF File (Adobe PDF File), 67 KB - mental_v7i6e15973_app3.pdf ]

## References

1. Lerman BI, Lewis SP, Lumley M, Grogan GJ, Hudson CC, Johnson E. Teen depression groups on Facebook: a content analysis. J Adolesc Res 2016 Oct 22;32(6):719-741. [doi: 10.1177/0743558416673717]
2. Gutowski E, White A, Liang B, Diamonti A, Berado D. How stress influences purpose development: the importance of social support. J Adolesc Res 2017 Oct 30;33(5):571-597. [doi: 10.1177/0743558417737754]
3. Subrahmanyam K, Lin G. Adolescents on the net: internet use and well-being. Adolescence 2007;42(168):659-677. [Medline: 18229503]

4. Baker R, White K. Predicting adolescents' use of social networking sites from an extended theory of planned behaviour perspective. Comput Hum Behav 2010 Nov;26(6):1591-1597 [FREE Full text] [doi: 10.1016/j.chb.2010.06.006]
5. Ponathil A, Agnisarman S, Khasawneh A, Narasimha S, Madathil KC. An Empirical Study Investigating the Effectiveness of Decision Aids in Supporting the Sensemaking Process on Anonymous Social Media. In: Proceedings of Human Factors and Ergonomics Society Annual Meeting. 2017 Presented at: HFES'17; October 9-13, 2017; Austin, TX p. 798-802 URL: https://journals.sagepub.com/doi/abs/10.1177/1541931213601693 [doi: 10.1177/1541931213601693]
6. Khasawneh A, Ponathil A, Ozkan NF, Madathil KC. How Should I Choose My Dentist? A Preliminary Study Investigating the Effectiveness of Decision Aids on Healthcare Online Review Portals. In: Proceedings of Human Factors and Ergonomics Society Annual Meeting. 2018 Presented at: HFES'18; October 1-5, 2018; Philadelphia, PA p. 1694-1698 URL: https://journals.sagepub.com/doi/abs/10.1177/1541931218621383 [doi: 10.1177/1541931218621383]
7. Lenhart A. Pew Research Center. 2009. Teens and Social Media: An Overview URL: https://www.pewresearch.org/internet/2009/04/10/teens-and-social-media-an-overview/ [accessed 2020-04-20]
8. Anderson M, Jiang J. Pew Research Center. 2018. Teens, Social Media & Technology URL: https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/ [accessed 2020-04-20]
9. Scharett E, Madathil K, Lopes S, Rogers H, Agnisarman S, Narasimha S, et al. An investigation of the information sought by caregivers of Alzheimer's patients on online peer support groups. Cyberpsychol Behav Soc Netw 2017 Oct;20(10):640-657. [doi: 10.1089/cyber.2017.0274] [Medline: 29039697]
10. Boyd D, Ellison N. Social network sites: definition, history, and scholarship. IEEE Eng Manag Rev 2010;38(3):16-31. [doi: 10.1109/EMR.2010.5559139]
11. Madathil KC, Greenstein JS, Juang KA, Neyens DM, Gramopadhye AK. An Investigation of the Informational Needs of Ovarian Cancer Patients and Their Supporters. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2013 Presented at: HFES'13; September 1, 2013; San Diego, CA p. 748-752 URL: https://journals.sagepub.com/doi/abs/10.1177/1541931213571163 [doi: 10.1177/1541931213571163]
12. Jackson S, Bailey M, Welles BF. #GirlsLikeUs: trans advocacy and community building online. New Media Soc 2017 Jun 9;20(5):1868-1888 [FREE Full text] [doi: 10.1177/1461444817709276]
13. Blackwell L, Hardy J, Ammari T, Veinot T, Lampe C, Schoenebeck S. LGBT Parents and Social Media: Advocacy, Privacy, and Disclosure during Shifting Social Movements. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2016 Presented at: CHI'16; May 7-12, 2016; San Jose, USA. [doi: 10.1145/2858036.2858342]
14. Gonzales AL. Disadvantaged minorities' use of the internet to expand their social networks. Communic Res 2015 Jan 13;44(4):467-486 [FREE Full text] [doi: 10.1177/0093650214565925]
15. Lawson CE. Platform vulnerabilities: harassment and misogynoir in the digital attack on Leslie Jones. Inf Commun Soc 2018 Feb 16;21(6):818-833. [doi: 10.1080/1369118x.2018.1437203]
16. Fritz N, Gonzales A. Privacy at the margins-not the normal trans story: negotiating trans narratives while crowdfunding at the margins. Int J Commun 2018;12:20 [FREE Full text]
17. Wood M, Rose E, Thompson C. Viral justice: online justice-seeking, intimate partner violence and affective contagion. Theor Criminol 2018 Jan 8;23(3):375-393. [doi: 10.1177/1362480617750507]
18. Page X, Wisniewski P, Knijnenburg B, Namara M. Social media's have-nots: an era of social disenfranchisement. Internet Res 2018 Oct 2;28(5):1253-1274 [FREE Full text] [doi: 10.1108/intr-03-2017-0123]
19. Linabary J, Corple D. Privacy for whom?: a feminist intervention in online research practice. Inf Commun Soc 2018 Feb 19;22(10):1447-1463. [doi: 10.1080/1369118X.2018.1438492]
20. Flores-Yeffal N, Vidales G, Martinez G. #WakeUpAmerica, #IllegalsAreCriminals: the role of the cyber public sphere in the perpetuation of the Latino cyber-moral panic in the US. Inf Commun Soc 2017 Oct 20;22(3):402-419 [FREE Full text] [doi: 10.1080/1369118x.2017.1388428]
21. Mitchell KJ, Wells M, Priebe G, Ybarra ML. Exposure to websites that encourage self-harm and suicide: prevalence rates and association with actual thoughts of self-harm and thoughts of suicide in the United States. J Adolesc 2014 Dec;37(8):1335-1344. [doi: 10.1016/j.adolescence.2014.09.011] [Medline: 25313930]
22. Guan L, Hao B, Cheng Q, Yip PS, Zhu T. Identifying chinese microblog users with high suicide probability using internet-based profile and linguistic features: classification model. JMIR Ment Health 2015;2(2):e17 [FREE Full text] [doi: 10.2196/mental.4227] [Medline: 26543921]
23. Hilton CH. Unveiling self-harm behaviour: what can social media site Twitter tell us about self-harm? A qualitative exploration. J Clin Nurs 2017 Jun;26(11-12):1690-1704. [doi: 10.1111/jocn.13575] [Medline: 27604049]
24. Zhu L, Westers NJ, Horton SE, King JD, Diederich A, Stewart SM, et al. Frequency of exposure to and engagement in nonsuicidal self-injury among inpatient adolescents. Arch Suicide Res 2016;20(4):580-590. [doi: 10.1080/13811118.2016.1162240] [Medline: 26983456]
25. Berry N, Bucci S, Lobban F. Use of the internet and mobile phones for self-management of severe mental health problems: qualitative study of staff views. JMIR Ment Health 2017 Nov 1;4(4):e52 [FREE Full text] [doi: 10.2196/mental.8311] [Medline: 29092809]
26. Jarvi S, Jackson B, Swenson L, Crawford H. The impact of social contagion on non-suicidal self-injury: a review of the literature. Arch Suicide Res 2013;17(1):1-19. [doi: 10.1080/13811118.2013.748404] [Medline: 23387399]

27. Insel BJ, Gould MS. Impact of modeling on adolescent suicidal behavior. Psychiatr Clin North Am 2008 Jun;31(2):293-316. [doi: 10.1016/j.psc.2008.01.007] [Medline: 18439450]
28. Gould M, Petrie K, Kleinman M, Wallenstein S. Clustering of attempted suicide: New Zealand national data. Int J Epidemiol 1994 Dec;23(6):1185-1189. [doi: 10.1093/ije/23.6.1185] [Medline: 7721521]
29. Cheng Q, Li H, Silenzio V, Caine ED. Suicide contagion: a systematic review of definitions and research utility. PLoS One 2014;9(9):e108724 [FREE Full text] [doi: 10.1371/journal.pone.0108724] [Medline: 25259604]
30. Young R, Subramanian R, Miles S, Hinnant A, Andsager JL. Social representation of cyberbullying and adolescent suicide: a mixed-method analysis of news stories. Health Commun 2017 Sep;32(9):1082-1092. [doi: 10.1080/10410236.2016.1214214] [Medline: 27566406]
31. Stack S. The effect of the media on suicide: evidence from Japan, 1955-1985. Suicide Life Threat Behav 1996;26(2):132-142. [Medline: 8840417]
32. Stack S. The media and suicide: a nonadditive model, 1968-1980. Suicide Life Threat Behav 1993;23(1):63-66. [Medline: 8475534]
33. Gould M, Jamieson P, Romer D. Media contagion and suicide among the young. Am Behav Sci 2016 Jul 27;46(9):1269-1284 [FREE Full text] [doi: 10.1177/0002764202250670]
34. Nock MK, Borges G, Bromet EJ, Cha CB, Kessler RC, Lee S. Suicide and suicidal behavior. Epidemiol Rev 2008;30:133-154 [FREE Full text] [doi: 10.1093/epirev/mxn002] [Medline: 18653727]
35. Purington A, Whitlock J. Non-suicidal self-injury in the media. Prev Res 2010;17(1):11-14 [FREE Full text]
36. Hawton K, Townsend E, Arensman E, Gunnell D, Hazell P, House A, et al. Psychosocial versus pharmacological treatments for deliberate self harm. Cochrane Database Syst Rev 2000(2):CD001764. [doi: 10.1002/14651858.CD001764] [Medline: 10796818]
37. Tellis GJ, MacInnis DJ, Tirunillai S, Zhang Y. What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence. J Mark 2019 Apr 24;83(4):1-20. [doi: 10.1177/0022242919841034]
38. Klingle K, van Vliet KJ. Self-compassion from the adolescent perspective: a qualitative study. J Adolesc Res 2017 Aug 14;34(3):323-346. [doi: 10.1177/0743558417722768]
39. Suicide Prevention Resource Center. 2006. Safe and Effective Messaging for Suicide Prevention URL: https://www.sprc.org/sites/default/files/migrate/library/SafeMessagingrevised.pdf [accessed 2020-04-20]
40. Kramer AD, Guillory JE, Hancock JT. Experimental evidence of massive-scale emotional contagion through social networks. Proc Natl Acad Sci U S A 2014 Jun 17;111(24):8788-8790 [FREE Full text] [doi: 10.1073/pnas.1320040111] [Medline: 24889601]
41. Harris IM, Roberts LM. Exploring the use and effects of deliberate self-harm websites: an internet-based study. J Med Internet Res 2013 Dec 20;15(12):e285 [FREE Full text] [doi: 10.2196/jmir.2802] [Medline: 24362563]
42. Lachmar E, Wittenborn A, Bogen K, McCauley H. #MyDepressionLooksLike: examining public discourse about depression on Twitter. JMIR Ment Health 2017 Oct 18;4(4):e43 [FREE Full text] [doi: 10.2196/mental.8141] [Medline: 29046270]
43. Hilton CE. 'It's the symptom of the problem, not the problem itself': a qualitative exploration of the role of pro-anorexia websites in users' disordered eating. Issues Ment Health Nurs 2018 Oct;39(10):865-875. [doi: 10.1080/01612840.2018.1493625] [Medline: 30307783]
44. Berrouiguet S, Larsen M, Mesmeur C, Gravey M, Billot R, Walter M, HUGOPSY Network, et al. Toward mhealth brief contact interventions in suicide prevention: case series from the suicide intervention assisted by messages (SIAM) randomized controlled trial. JMIR Mhealth Uhealth 2018 Jan 10;6(1):e8 [FREE Full text] [doi: 10.2196/mhealth.7780] [Medline: 29321126]
45. Schlichthorst M, King K, Turnure J, Sukunesan S, Phelps A, Pirkis J. Influencing the conversation about masculinity and suicide: evaluation of the man up multimedia campaign using Twitter data. JMIR Ment Health 2018 Feb 15;5(1):e14 [FREE Full text] [doi: 10.2196/mental.9120] [Medline: 29449203]
46. Robert A, Suelves JM, Armayones M, Ashley S. Internet use and suicidal behaviors: internet as a threat or opportunity? Telemed J E Health 2015 Apr;21(4):306-311. [doi: 10.1089/tmj.2014.0129] [Medline: 25654489]
47. Luxton DD, June JD, Fairall JM. Social media and suicide: a public health perspective. Am J Public Health 2012 May;102(Suppl 2):S195-S200. [doi: 10.2105/AJPH.2011.300608] [Medline: 22401525]
48. Wong QJ, Werner-Seidler A, Torok M, van Spijker B, Calear AL, Christensen H. Service use history of individuals enrolling in a web-based suicidal ideation treatment trial: analysis of baseline data. JMIR Ment Health 2019 Apr 2;6(4):e11521 [FREE Full text] [doi: 10.2196/11521] [Medline: 30938686]
49. Livingstone S, Smith P. Annual research review: harms experienced by child users of online and mobile technologies: the nature, prevalence and management of sexual and aggressive risks in the digital age. J Child Psychol Psychiatry 2014 Jun;55(6):635-654. [doi: 10.1111/jcpp.12197] [Medline: 24438579]
50. Pater J, Mynatt E. Jessica Pater. 2017. Defining Digital Self-Harm URL: http://jesspater.com/wp-content/uploads/2014/12/CSCW-2017-FINAL.pdf [accessed 2020-04-08]
51. Lewis S, Seko Y. A double-edged sword: a review of benefits and risks of online nonsuicidal self-injury activities. J Clin Psychol 2016 Mar;72(3):249-262. [doi: 10.1002/jclp.22242] [Medline: 26613372]

52. Patton GC, Coffey C, Romaniuk H, Mackinnon A, Carlin JB, Degenhardt L, et al. The prognosis of common mental disorders in adolescents: a 14-year prospective cohort study. Lancet 2014 Apr 19;383(9926):1404-1411. [doi: 10.1016/S0140-6736(13)62116-9] [Medline: 24439298]
53. Muñoz-Sánchez JL, Delgado C, Parra-Vidales E, Franco-Martín M. Facilitating factors and barriers to the use of emerging technologies for suicide prevention in Europe: multicountry exploratory study. JMIR Ment Health 2018 Jan 24;5(1):e7 [FREE Full text] [doi: 10.2196/mental.7784] [Medline: 29367183]
54. Mukhra R, Baryah N, Krishan K, Kanchan T. 'Blue whale challenge': a game or crime? Sci Eng Ethics 2019 Feb;25(1):285-291. [doi: 10.1007/s11948-017-0004-2] [Medline: 29129013]
55. Thaploo M. U4UVoice. 2017. Blue Whale: Jammu Techie Has Decoded the Mystery-5 Important Points URL: https://u4uvoice.com/blue-whale-jammu-techie-has-decoded-the-mystery-5-important-points/ [accessed 2018-10-17]
56. Maina A. Small Business Trends. 2016. 20 Popular Social Media Sites Right Now URL: https://smallbiztrends.com/2016/05/popular-social-media-sites.html [accessed 2018-11-28]
57. Clarke V, Braun V. Teaching thematic analysis: overcoming challenges and developing strategies for effective learning. Psychologist 2013;26(2):120-123 [FREE Full text]
58. Pater J, Haimson O, Andalibi N, Mynatt E. 'Hunger Hurts but Starving Works': Characterizing the Presentation of Eating Disorders Online. In: Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing. 2016 Presented at: CSCW'16; February 27-March 2, 2016; San Francisco, USA URL: https://dl.acm.org/citation.cfm?id=2820030 [doi: 10.1145/2818048.2820030]
59. Pater J, Miller A, Mynatt E. This Digital Life: A Neighborhood-Based Study of Adolescents' Lives Online. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. 2015 Presented at: CHI'15; April 18, 2015; Seoul Republic of Korea URL: https://dl.acm.org/citation.cfm?id=2702534 [doi: 10.1145/2702123.2702534]
60. YouTube Creator Academy. Search and Discovery on YouTube URL: https://creatoracademy.youtube.com/page/lesson/discovery [accessed 2019-11-06]
61. Covington P, Adams J, Sargin E. Deep Neural Networks for YouTube Recommendations. In: Proceedings of the 10th ACM Conference on Recommender Systems. 2016 Presented at: RecSys'16; September 15-17, 2016; Boston, MA, USA. [doi: 10.1145/2959100.2959190]
62. Saunders B, Sim J, Kingstone T, Baker S, Waterfield J, Bartlam B, et al. Saturation in qualitative research: exploring its conceptualization and operationalization. Qual Quant 2018;52(4):1893-1907 [FREE Full text] [doi: 10.1007/s11135-017-0574-8] [Medline: 29937585]
63. Fusch P, Ness L. NSUWorks - Nova Southeastern University. 2015. Are We There Yet? Data Saturation in Qualitative Research URL: http://nsuworks.nova.edu/tqr/vol20/iss9/3/ [accessed 2018-11-13]
64. Bromberg JE, Augustson EM, Backinger CL. Portrayal of smokeless tobacco in YouTube videos. Nicotine Tob Res 2012 Apr;14(4):455-462 [FREE Full text] [doi: 10.1093/ntr/ntr235] [Medline: 22080585]
65. Richardson A, Vallone DM. YouTube: a promotional vehicle for little cigars and cigarillos? Tob Control 2014 Jan;23(1):21-26. [doi: 10.1136/tobaccocontrol-2012-050562] [Medline: 23047887]
66. Luo C, Zheng X, Zeng DD, Leischow S. Portrayal of electronic cigarettes on YouTube. BMC Public Health 2014 Oct 3;14:1028 [FREE Full text] [doi: 10.1186/1471-2458-14-1028] [Medline: 25277872]
67. Web Analytics World. Radian 6 Overview URL: https://www.webanalyticsworld.net/analytics-measurement-and-management-tools/radian-6-overview [accessed 2018-11-28]
68. Laine M, Frühwirth C. Monitoring Social Media: Tools, Characteristics and Implications. In: Proceedings of the International Conference of Software Business. 2010 Presented at: ICSOB'10; June 21-23, 2010; Jyväskylä, Finland. [doi: 10.1007/978-3-642-13633-7_19]
69. Khattar A, Dabas K, Gupta K, Chopra S, Kumaraguru P. arXiv. 2018. White or Blue, The Whale gets its Vengeance: A Social Media Analysis of the Blue Whale Challenge URL: http://arxiv.org/abs/1801.05588 [accessed 2019-09-08]
70. Saldana J. The Coding Manual for Qualitative Researchers. Thousand Oaks, California: Sage Publications; 2015.
71. ATLAS.ti: The No 1 Software for Qualitative and Mixed Methods Data Analysis. URL: https://atlasti.com/ [accessed 2019-11-06]
72. Chambers DA, Pearson JL, Lubell K, Brandon S, O'brien K, Zinn J. The science of public messages for suicide prevention: a workshop summary. Suicide Life Threat Behav 2005 Apr;35(2):134-145. [doi: 10.1521/suli.35.2.134.62871] [Medline: 15843331]
73. US Department of Health and Human Services. National Strategy for Suicide Prevention: Goals and Objectives for Action. Scotts Valley, California, US: CreateSpace Independent Publishing; 2010.
74. Stone DM, Simon TR, Fowler KA, Kegler SR, Yuan K, Holland KM, et al. Vital signs: trends in state suicide rates-United States, 1999-2016 and circumstances contributing to suicide-27 states, 2015. MMWR Morb Mortal Wkly Rep 2018 Jun 8;67(22):617-624 [FREE Full text] [doi: 10.15585/mmwr.mm6722a1] [Medline: 29879094]
75. Baldessarini RJ, Tondo L, Hennen J. Effects of lithium treatment and its discontinuation on suicidal behavior in bipolar manic-depressive disorders. J Clin Psychiatry 1999;60(Suppl 2):77-84; discussion 111 [FREE Full text] [Medline: 10073392]

76. Fekete S, Schmidtke A. The impact of mass media reports on suicide and attitudes toward self-destruction: previous studies and some new data from Hungary and Germany. In: Mishara BL, editor. The Impact of Suicide (Springer Series on Death and Suicide). New York, USA: Springer Publishing; 1995:142-155.
77. Cialdini RB. Crafting normative messages to protect the environment. Curr Dir Psychol Sci 2016 Jun 22;12(4):105-109. [doi: 10.1111/1467-8721.01242]
78. Jacobs D. The Harvard Medical School Guide to Suicide Assessment and Intervention. San Francisco, California: Jossey-Bass; 1999.
79. Fekete S, Macsai E. Hungarian suicide models, past and present. In: Ferrari G, editor. Suicidal Behavior and Risk Factors. Bologna: Monduzzi Editore; 1990:149-156.
80. Sonneck G, Etzersdorfer E, Nagel-Kuess S. Imitative suicide on the Viennese subway. Soc Sci Med 1994 Feb;38(3):453-457. [doi: 10.1016/0277-9536(94)90447-2] [Medline: 8153751]
81. Recupero PR, Harms SE, Noble JM. Googling suicide: surfing for suicide information on the internet. J Clin Psychiatry 2008 Jun;69(6):878-888. [Medline: 18494533]
82. Armstrong G, Vijayakumar L, Niederkrotenthaler T, Jayaseelan M, Kannan R, Pirkis J, et al. Assessing the quality of media reporting of suicide news in India against World Health Organization guidelines: a content analysis study of nine major newspapers in Tamil Nadu. Aust N Z J Psychiatry 2018 Sep;52(9):856-863. [doi: 10.1177/0004867418772343] [Medline: 29726275]
83. Noble-Carr D, Woodman E. Considering identity and meaning constructions for vulnerable young people. J Adolesc Res 2016 Dec 28;33(6):672-698. [doi: 10.1177/0743558416684952]
84. Gould MS, Shaffer D. The impact of suicide in television movies. Evidence of imitation. N Engl J Med 1986 Sep 11;315(11):690-694. [doi: 10.1056/NEJM198609113151107] [Medline: 3748073]
85. Lewis S. CBS News. 2019. Police Issue Warning to Parents After 'Momo Challenge' Resurfaces URL: https://www.cbsnews.com/news/momo-challenge-resurfaces-police-issue-warning-to-parents/ [accessed 2020-02-15]
86. Tanner MA, Murray JA, Phillips DP. The impact of televised movies about suicide. N Engl J Med 1988 Mar 17;318(11):707-708. [doi: 10.1056/NEJM198803173181112] [Medline: 3344023]
87. Cooper Jr MT, Bard D, Wallace R, Gillaspy S, Deleon S. Suicide attempt admissions from a single children's hospital before and after the introduction of Netflix series 13 reasons why. J Adolesc Health 2018 Dec;63(6):688-693. [doi: 10.1016/j.jadohealth.2018.08.028] [Medline: 30454731]
88. Ayers JW, Althouse BM, Leas EC, Dredze M, Allem J. Internet searches for suicide following the release of 13 reasons why. JAMA Intern Med 2017 Oct 1;177(10):1527-1529 [FREE Full text] [doi: 10.1001/jamainternmed.2017.3333] [Medline: 28759671]
89. Ortiz P, Khin EK. Traditional and new media's influence on suicidal behavior and contagion. Behav Sci Law 2018 Mar;36(2):245-256. [doi: 10.1002/bsl.2338] [Medline: 29659071]
90. Roth R, Abraham J, Zinzow H, Wisniewski P, Khasawneh A, Chalil Madathil K. Evaluating News Media Reports on the 'Blue Whale Challenge' for Adherence to Suicide Prevention Safe Messaging Guidelines. Proc. ACM Hum.-Comput. Interact 2020 May 28;4(CSCW1):1-27. [doi: 10.1145/3392831]
91. Arendt F, Scherr S, Till B, Prinzellner Y, Hines K, Niederkrotenthaler T. Suicide on TV: minimising the risk to vulnerable viewers. Br Med J 2017 Aug 22;358:j3876. [doi: 10.1136/bmj.j3876] [Medline: 28830886]
92. Hong V, Ewell Foster CJ, Magness CS, McGuire TC, Smith PK, King CA. 13 reasons why: viewing patterns and perceived impact among youths at risk of suicide. Psychiatr Serv 2019 Feb 1;70(2):107-114. [doi: 10.1176/appi.ps.201800384] [Medline: 30453859]
93. Zimerman A, Caye A, Zimerman A, Salum GA, Passos IC, Kieling C. Revisiting the werther effect in the 21st century: bullying and suicidality among adolescents who watched 13 reasons why. J Am Acad Child Adolesc Psychiatry 2018 Aug;57(8):610-3.e2. [doi: 10.1016/j.jaac.2018.02.019] [Medline: 30071982]
94. Vaterlaus JM, Tulane S, Porter BD, Beckert TE. The perceived influence of media and technology on adolescent romantic relationships. J Adolesc Res 2017 May 31;33(6):651-671. [doi: 10.1177/0743558417712611]
95. Swendeman D, Arnold E, Harris D, Fournier J, Comulada W, Reback C, Adolescent Medicine Trials Network (ATN) CARES Team. Text-messaging, online peer support group, and coaching strategies to optimize the HIV prevention continuum for youth: protocol for a randomized controlled trial. JMIR Res Protoc 2019 Aug 9;8(8):e11165 [FREE Full text] [doi: 10.2196/11165] [Medline: 31400109]
96. Madathil KC, Rivera-Rodriguez AJ, Greenstein JS, Gramopadhye AK. Healthcare information on YouTube: a systematic review. Health Informatics J 2015 Sep;21(3):173-194. [doi: 10.1177/1460458213512220] [Medline: 24670899]
97. Khasawneh A, Madathil KC, Dixon E, Wisniewski P, Zinzow H, Roth R. An Investigation on the Portrayal of Blue Whale Challenge on YouTube and Twitter. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2019 Presented at: HFES'19; October 28-November 1, 2019; Seattle, WA p. 887-888. [doi: 10.1177/1071181319631179]
98. Khasawneh A. Tiger Prints. 2019. Systems Engineering Approaches to Minimize the Viral Spread of Social Media Challenges URL: https://tigerprints.clemson.edu/all_dissertations/2526 [accessed 2020-04-20]

99. Khasawneh K, Ozsoy M, Donovick C, Ghazaleh NA, Ponomarev D. EnsembleHMD: accurate hardware malware detectors with specialized ensemble classifiers. IEEE Trans Dependable and Secure Comput 2018:1-1 (forthcoming)(forthcoming) [FREE Full text] [doi: 10.1109/TDSC.2018.2801858]
100. Khasawneh K, Ozsoy M, Donovick C. Ensemble Learning for Low-Level Hardware-Supported Malware Detection. In: Proceedings of the International Symposium on Recent Advances in Intrusion Detection. 2015 Presented at: RAID'15; November 2-4, 2015; Kyoto, Japan p. 2-24 URL: https://link.springer.com/chapter/10.1007/978-3-319-26362-5_ [doi: 10.1007/978-3-319-26362-5_1]

## Abbreviations

**NSSI:** nonsuicidal self-injury
**SPRC:** Suicide Prevention Resource Center

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Editorial

# Digital Mental Health: The Answer to the Global Mental Health Crisis?

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## Abstract

Digital mental health interventions are often touted as the solution to the global mental health crisis. However, moving mental health care from the hands of professionals and into digital apps may further isolate individuals who need human connection the most. In this commentary, we argue that people, our society's greatest resource, are as ubiquitous as technology. Thus, we argue that research focused on using technology to support all people in delivering mental health prevention and intervention deserves greater attention in the coming decade.

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**KEYWORDS**

public mental health; universal mental health prevention; digital implementation support

## Introduction

Mental health is public health. Depression is a leading cause of disability worldwide and is estimated to affect 264 million people globally [1]. Every day 129 Americans die by suicide and 130 die by opioid overdose [2,3]. For nearly every leading cause of death (eg, cancer, heart disease), comorbid mental health disorders increase morbidity and mortality rates. For example, heart disease is the leading cause of death in the United States. Depression increases the risk for coronary heart disease among healthy adults [4,5] and mortality among patients with coronary heart disease [5,6]. To address global public health, we must address mental health.

A comprehensive public health response to disease elimination requires the use of three interrelated services that span prevention and intervention. These three services include universal prevention to limit the development of the disease, targeted intervention among those at greatest risk for acquiring the disease, and intensive intervention to treat those already experiencing the disease. The dominant paradigm for promoting mental health in society is the provision of clinical services to individuals in specialized mental health care facilities, which represents an intensive public health intervention. However, most people in the world with a mental health disorder receive no treatment [7]. Among people who actually receive care, few receive an effective treatment. For example, only 16.5% of people with major depressive disorder receive minimally adequate treatment globally [8]. Although the causes of this treatment-use gap are multifactorial, it is partly due to the dramatic shortage of specialty mental health care providers. The supply of mental health professionals does not meet the demand for mental health care. By 2025, the United States is projected to have shortages in nearly every type of mental health care provider (eg, psychiatrist, psychologist, social worker) [9]. Mental health workforce shortages are even more profound in low- and middle-income countries. The median number of psychiatrists available per 100,000 individuals in high-income countries is 172 times greater than in low-income countries, where there is approximately 0.05 psychiatrists per 100,000 individuals [10]. We require novel models of intervention delivery [11] as well as a paradigm shift toward a comprehensive public mental health response [12] if we are to overcome this global mental health crisis.

A total of 90% of American adults use the internet [13] and 96% own a cellphone [14]. The global penetration rate of the internet is 53%, and although the lowest rates are among Central Africa and Southern Asia, these regions are also experiencing the fastest growth [15]. Widely celebrated as the solution to the supply and demand imbalance in mental health care, digital mental health interventions have flooded the market place to supplement specialty mental health care. However, the evidence supporting their efficacy is mixed [16,17], and engagement with digital mental health interventions, particularly mobile apps that lack ancillary human interaction, is abysmal [18]. Users are unlikely to use these interventions more than a few times. Particularly concerning is the fact that some digital mental health apps share user data without disclosing this in their privacy policy [19]. Furthermore, the movement of specialty mental health care, an intensive public health intervention, from the hands of clinicians and into standalone digital interventions ignores decades of research about the importance of social support and may further isolate individuals who need human connection the most. Given the robust social support literature, it is not surprising that digital interventions with the highest levels of engagement are those that include some form of human interaction [20,21]. In this commentary, we argue for a renewed focus on universal mental health prevention and targeted intervention [22]. We propose that *people*, our society's greatest resource, are as ubiquitous as technology. Thus, research focused on using technology to support *all people* in their delivery of universal prevention and targeted intervention deserves greater attention in the coming decade. We believe that it is the synergy of people and technology that will allow us to overcome the global mental health crisis, not technology alone.

## The Way Forward

To date, multiple systematic reviews and meta-analytic studies demonstrate that lay health workforces (ie, community members without advanced mental health care training) can deliver effective mental health care, including effectively screening for mental health disorders and providing psychosocial treatments for the most common psychiatric disorders [23,24]. Given the evidence supporting the use of community members in the delivery of targeted and intensive mental health interventions, we envision enabling community members to deliver all forms of public mental health interventions. This includes supporting all people in the delivery of universal interventions through their provision of social support, as well as supporting the delivery of targeted interventions. Specifically, lay individuals in the community can help identify when their loved ones or fellow community members are distressed or in crisis, provide that identified person with evidence-based support, and escalate that person to appropriate levels of care when it is needed. Shifting the work of mental health promotion to all people is the kind of universal public mental health strategy needed to move the needle [22] and attenuate the stigma associated with mental health disorders. Our efforts need to parallel our efforts to solve other public health crises. We need mental health prevention and intervention to be like fluoride in the water—it needs to be everywhere. Given the ubiquity of people, the synergy of people empowered by technology may be the answer that provides a solution to our global mental health crisis.

To advance these efforts, we make the following suggestions:

First, all people need to be able to reliably identify when their loved one or fellow community member is in need of help. There are both active and passive ways to accomplish this goal. An active strategy may involve the dissemination of online trainings that teach all people to recognize the difference between stress, distress, and crisis, aligned with popular gatekeeper trainings [25]. However, there are also more passive strategies that harness technology. Work is underway to use data naturally available in text messages and social media to reliably predict mood states [26], including Facebook's work to develop an algorithm to predict and prevent suicide among its users [27,28]. These innovative models could eventually support people in identifying mood states in their loved ones. Perhaps in the future our cell phones can notify us when our loved one is engaging in a text message conversation reflective of an urge to use opioids.

Second, we need to distill the active ingredients of our most robust evidence-based practices into core strategies that are ready for dissemination to the public. Identification of problems must be tied to actionable and clear steps and interventions. Thus, as we develop ways for all people to identify stress, distress, and crisis in their loved ones and community members, each category must be connected to evidence-based interventions, including when to connect that person to a higher level of care. To do that, we first need to establish which evidence-based strategies are appropriate for all people to use. Perhaps our cell phones can suggest that we provide our loved one with the National Suicide Prevention Hotline number or call 911 when a loved one is in crisis. When a loved one is stressed or distressed, perhaps our cell phones can coach a friend or family member to use low-intensity evidence-based techniques, such as active listening, problem solving, and behavioral activation as was used in the *Atmiyata* trial among community volunteers to promote wellness and reduce distress in India [29].

Third, we need to identify the best platform for disseminating and implementing the key elements of this proposed public mental health approach. One avenue could be the public education system. Public education curriculum increasingly includes information regarding physical health promotion (eg, health eating and exercise); thus, this may be an appropriate setting for learning about mental health promotion in oneself and others. In addition, as we continue to invest in patient-facing digital interventions to promote mental health, so too should we consider investing in clinician- or support-person-facing digital implementation supports. A notable example of this work includes Naslund, Shidhaye, and Patel's [30] work to harness digital technology to build capacity for the implementation of evidence-based mental health intervention in nonspecialist health workers. Technology such as this could be adapted and refined so that it can be used to support all people in supporting their loved ones and community members.

Fourth, this work will require attending to several important ethical considerations. Providing mental health support places deliverers at an increased risk for experiencing secondary stress. Encouraging people to ask and provide care might meaningfully increase our population’s experience with secondary stress. Suffering is human, but often people are uncomfortable sitting with the discomfort and suffering of others. Furthermore, this work begs the question of who is responsible for providing support. Is a loved one partially responsible for incidents that occur when they did not respond to their cell phone’s notification? We posit that, for the most part, friends, family, and community members already worry about the health and safety of their friends, family, and community members, and often feel responsible when incidents occur. To overcome this, we want to ensure that everyone has the tools to intervene, rather than unproductively worry, when they are ready and willing. Furthermore, safeguards must be in place to prevent information collected via technology or when a friend intervenes from causing harm (eg, employment discrimination). Thus, privacy concerns must be addressed. For example, one might argue that surveillance data collected to predict high-risk behaviors, like suicidal behavior on Facebook, is protected health information and should, therefore, be subject to regulatory oversight.

To solve the mental health crisis, we need innovative and expansive solutions, and we believe that harnessing the power of people in mental health prevention and intervention delivery, supported by technology, may get us one step closer to improving public mental health.

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## Conflicts of Interest

RSB receives royalties from Oxford University Press and has consulted for Merck and the Camden Coalition for Healthcare Providers.

## References

1. GBD 2017 Disease and Injury Incidence and Prevalence Collaborators. Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. Lancet 2018 Nov;392(10159):1789-1858. [doi: 10.1016/S0140-6736(18)32279-7]
2. Centers for Disease Control and Prevention. 2020. America's drug overdose epidemic: data to action URL: https://www.cdc.gov/injury/features/prescription-drug-overdose/index.html
3. American Foundation for Suicide Prevention. 2020. Suicide Statistics URL: https://afsp.org/about-suicide/suicide-statistics/
4. Pan A, Sun Q, Okereke OI, Rexrode KM, Hu FB. Depression and risk of stroke morbidity and mortality: a meta-analysis and systematic review. JAMA 2011 Sep 21;306(11):1241-1249 [FREE Full text] [doi: 10.1001/jama.2011.1282] [Medline: 21934057]
5. Shi S, Liu T, Liang J, Hu D, Yang B. Depression and risk of sudden cardiac death and arrhythmias. Psychosom Med 2017:1. [doi: 10.1097/psy.0000000000000382]
6. Barth J, Schumacher M, Herrmann-Lingen C. Depression as a risk factor for mortality in patients with coronary heart disease: a meta-analysis. Psychosom Med 2004;66(6):802-813. [doi: 10.1097/01.psy.0000146332.53619.b2] [Medline: 15564343]
7. Wang PS, Aguilar-Gaxiola S, Alonso J, Angermeyer MC, Borges G, Bromet EJ, et al. Use of mental health services for anxiety, mood, and substance disorders in 17 countries in the WHO world mental health surveys. Lancet 2007 Sep;370(9590):841-850. [doi: 10.1016/S0140-6736(07)61414-7]
8. Thornicroft G, Chatterji S, Evans-Lacko S, Gruber M, Sampson N, Aguilar-Gaxiola S, et al. Undertreatment of people with major depressive disorder in 21 countries. Br J Psychiatry 2017 Feb;210(2):119-124 [FREE Full text] [doi: 10.1192/bjp.bp.116.188078] [Medline: 27908899]
9. Health Resources and Services Administration/National Center for Health Workforce Analysis; Substance Abuse and Mental Health Services Administration/Office of Policy, Planning, and Innovation. National projections of supply and demand for behavioral health practitioners: 2013-2025. HRSA 2015. [doi: 10.1037/e476292006-001]
10. Kakuma R, Minas H, van Ginneken N, Dal Poz MR, Desiraju K, Morris JE, et al. Human resources for mental health care: current situation and strategies for action. Lancet 2011 Nov;378(9803):1654-1663. [doi: 10.1016/s0140-6736(11)61093-3]

11. Kazdin AE. Annual research review: expanding mental health services through novel models of intervention delivery. J Child Psychol Psychiatr 2018 Jun 13;60(4):455-472. [doi: 10.1111/jcpp.12937]
12. Atkins MS, Frazier SL. Expanding the toolkit or changing the paradigm: are we ready for a public health approach to mental health? Perspect Psychol Sci 2011 Sep;6(5):483-487. [doi: 10.1177/1745691611416996] [Medline: 26168200]
13. Pew Research Center. 2019. Internet/broadband fact sheet URL: https://www.pewresearch.org/internet/fact-sheet/internet-broadband/ [accessed 2020-02-13]
14. Pew Research Center. 2019. Mobile fact sheet URL: https://www.pewresearch.org/internet/fact-sheet/mobile/ [accessed 2020-02-13]
15. Kemp S. We Are Social. 2018 Jan 30. Digital in 2018: world's internet users pass the 4 billion mark URL: https://wearesocial.com/blog/2018/01/global-digital-report-2018
16. Weisel K, Fuhrmann L, Berking M, Baumeister H, Cuijpers P, Ebert D. Standalone smartphone apps for mental health-a systematic review and meta-analysis. NPJ Digit Med 2019;2:118 [FREE Full text] [doi: 10.1038/s41746-019-0188-8] [Medline: 31815193]
17. Firth J, Torous J, Nicholas J, Carney R, Rosenbaum S, Sarris J. Can smartphone mental health interventions reduce symptoms of anxiety? A meta-analysis of randomized controlled trials. J Affect Disord 2017 Aug 15;218:15-22. [doi: 10.1016/j.jad.2017.04.046] [Medline: 28456072]
18. Torous J, Nicholas J, Larsen ME, Firth J, Christensen H. Clinical review of user engagement with mental health smartphone apps: evidence, theory and improvements. Evid Based Ment Health 2018 Aug;21(3):116-119. [doi: 10.1136/eb-2018-102891] [Medline: 29871870]
19. Huckvale K, Torous J, Larsen ME. Assessment of the data sharing and privacy practices of smartphone apps for depression and smoking cessation. JAMA Netw Open 2019 Apr 05;2(4):e192542. [doi: 10.1001/jamanetworkopen.2019.2542] [Medline: 31002321]
20. Kim H, Ray CD, Veluscek AM. Complementary support from facilitators and peers for promoting mhealth engagement and weight loss. J Health Commun 2017 Nov;22(11):905-912. [doi: 10.1080/10810730.2017.1373876] [Medline: 29125393]
21. Piette JD, Marinec N, Janda K, Morgan E, Schantz K, Yujra ACA, et al. Structured caregiver feedback enhances engagement and impact of mobile health support: a randomized trial in a lower-middle-income country. Telemed J E Health 2016 Apr;22(4):261-268 [FREE Full text] [doi: 10.1089/tmj.2015.0099] [Medline: 26352854]
22. Purtle J, Nelson KL, Counts NZ, Yudell M. Population-based approaches to mental health: history, strategies, and evidence. Annu Rev Public Health 2020 Apr 02;41:201-221. [doi: 10.1146/annurev-publhealth-040119-094247] [Medline: 31905323]
23. Barnett ML, Gonzalez A, Miranda J, Chavira DA, Lau AS. Mobilizing community health workers to address mental health disparities for underserved populations: a systematic review. Adm Policy Ment Health 2018 Mar;45(2):195-211 [FREE Full text] [doi: 10.1007/s10488-017-0815-0] [Medline: 28730278]
24. Singla DR, Kohrt BA, Murray LK, Anand A, Chorpita BF, Patel V. Psychological treatments for the world: lessons from low- and middle-income countries. Annu Rev Clin Psychol 2017 May 08;13:149-181 [FREE Full text] [doi: 10.1146/annurev-clinpsy-032816-045217] [Medline: 28482687]
25. Burnette C, Ramchand R, Ayer L. Gatekeeper training for suicide prevention: a theoretical model and review of the empirical literature. Rand Health Q 2015 Jul 15;5(1):16 [FREE Full text] [Medline: 28083369]
26. Zulueta J, Piscitello A, Rasic M, Easter R, Babu P, Langenecker SA, et al. Predicting mood disturbance severity with mobile phone keystroke metadata: a biaffect digital phenotyping study. J Med Internet Res 2018 Jul 20;20(7):e241. [doi: 10.2196/jmir.9775] [Medline: 30030209]
27. Facebook. 2020. Suicide prevention URL: https://www.facebook.com/help/594991777257121
28. Tsukayama H. The Washington Post. 2017 Nov 27. Facebook is using AI to try to prevent suicide URL: https://www.washingtonpost.com/news/the-switch/wp/2017/11/27/facebook-is-using-ai-to-try-to-prevent-suicide/
29. Shields-Zeeman L, Pathare S, Walters BH, Kapadia-Kundu N, Joag K. Promoting wellbeing and improving access to mental health care through community champions in rural India: the intervention approach. Int J Ment Health Syst 2017;11:6. [doi: 10.1186/s13033-016-0113-3] [Medline: 28066505]
30. Naslund JA, Shidhaye R, Patel V. Digital technology for building capacity of nonspecialist health workers for task sharing and scaling up mental health care globally. Harvard Rev Psychiatry 2019;27(3):181-192. [doi: 10.1097/hrp.0000000000000217]

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Original Paper

# Mobile App Integration Into Dialectical Behavior Therapy for Persons With Borderline Personality Disorder: Qualitative and Quantitative Study

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## Abstract

**Background:** The advancement of and access to technology such as smartphones has implications for psychotherapeutic health care and how interventions for a range of mental health disorders are provided.

**Objective:** The objective of this study was to describe the experiences of participants while using a mobile phone app that was designed to enhance and support dialectical behavior therapy for personality disorders.

**Methods:** A combination of in-depth interviews and questionnaires were used to capture the experiences of participants who used the app while undergoing dialectical behavior therapy treatment. A mixed methods approach was used; qualitative data from the interviews were analyzed using thematic analysis and were combined with quantitative data from the questionnaires.

**Results:** Participants (N=24) who were receiving dialectical behavior therapy used the trial app. Participants (n=20) completed an evaluation questionnaire and a subset of this group (n=8) participated in semistructured interviews. Major themes that were identified from the interviews were (1) an overall positive experience of using the app—participants perceived that the app facilitated access and implementation of dialectical behavior therapy strategies (to regulate mood and behavior in challenging situations)—and (2) that the app provided a common source of information for patient and therapist interactions—app-based interactions were perceived to facilitate therapeutic alliance. Qualitative themes from the interviews were largely congruent with the quantitative responses from the questionnaires.

**Conclusions:** Participants welcomed the integration of technology as a supplement to clinical treatment. The app was perceived to facilitate and support many of the therapeutic techniques associated with dialectical behavior therapy treatment. The incorporation of technology into psychotherapeutic interventions may facilitate the transfer of knowledge and strategies that are learned in therapy to use in real-world settings thereby promoting recovery from mental health problems.

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**KEYWORDS**

dialectical behavior therapy; mobile application; blended intervention; mHealth; app

## Introduction

Borderline personality disorder is one of the most prevalent personality disorders in clinical populations [1] and has traditionally been considered difficult to treat [2]. There are a range of structured psychotherapeutic interventions that are considered effective in treating borderline personality disorder [3-5] including dialectical behavior therapy [6,7]. While dialectical behavior therapy is an evidence-based treatment for borderline personality disorder, it has been acknowledged that certain improvements such as reducing dropout rates and improving clinical implementation would benefit treatment effectiveness [8-10].

Advancement of and improved access to technologies such as the internet and mobile apps have led to the examination of how these technologies may supplement and improve the effectiveness of psychotherapeutic interventions [11]. The use of mobile-based interventions can have a number of advantages; mobile-based interventions may facilitate access to evidence-based treatment, enhance the potency of psychotherapy, reduce stigma associated with psychotherapy, enable users to work at their own pace, promote autonomy, and flexibly integrate mental health interventions without local or temporal boundaries into daily life [12-14]. A key component of successful implementation of a mobile app regardless of type of therapeutic intervention is user engagement [15].

Despite a number of potential benefits, there are also a number of concerns such as hacking and the illegal use of personal data, ensuring the quality of the therapeutic interventions that use this technology, the identification and response to adverse events and the impact of technological problems on clinical management and duty of care within vulnerable populations [14,16].

Dialectical behavior therapy is concerned with helping people to increase their emotional and cognitive control through a variety of techniques such as monitoring one’s mood and implementing appropriate strategies in difficult situations. Being able to access strategies outside of therapy in a range of situations is an important component that is necessary to facilitate therapeutic change. Thus, both active engagement in treatment and a good therapeutic alliance are the underpinnings of effective dialectical behavior therapy treatment. Engagement can be a challenge in dialectical behavior therapy treatment and several studies have noted dropout rates between 20 and 50% [9.10]. Dropout from treatment has been associated with a higher risk of self-injury and suicide within this population [17].

The integration of a mobile app into dialectical behavior therapy treatment is congruent with the goals and techniques of psychotherapy for borderline personality disorder. It is hypothesized that the integration of an app into dialectical behavior therapy treatment will facilitate the use of appropriate therapeutic techniques and reduce dropout. A recent study on dialectical behavior therapy found that using dialectical behavior therapy skills less was linked to higher dropout from treatment and that more frequent of use dialectical behavior therapy skills was associated with less self-harm [17].

Currently, there are only a few studies that have examined how mobile apps can be integrated into dialectical behavior therapy treatment for borderline personality disorders [18-21]. Results from these studies have indicated the potential feasibility of using apps in dialectical behavior therapy treatment, but these studies also concluded that further research was needed.

The aim of the study was to identify participant perspectives on dialectical behavior therapy treatment and the use of a mobile app as a tool to enhance and support this therapy. Specifically, the study was designed to capture the experiences of participants who used the app during their dialectical behavior therapy treatment and their perceptions of using the app to facilitate therapeutic goals in treatment.

## Methods

### Participants

Participants were recruited from two psychiatric outpatient clinics located in Region Zealand, Denmark. Participants were invited to participate in the study if they met the inclusion criteria of a primary diagnosis of personality disorder (ICD-10 definition) and being able to participate in group treatment that used a dialectical behavior therapy framework. Several groups were used in order to capture a range of therapist, patient, and group characteristics.

### Treatment

Dialectical behavior therapy [7] has a solid evidence base that demonstrates its effectiveness in treating personality disorders. The therapy was initially developed to help patients with self-injurious and suicidal behavior [7], but it has been adapted for broader clinical application (such as for treatment in emotional instability or substance abuse problems)[7].

Dialectical behavior therapy has its roots in cognitive behavior therapy and focuses on changing unhelpful behavioral patterns by acknowledging feelings, thoughts, and behaviors. The primary dialectical principle in the therapy is that one needs to accept circumstances while working toward change. Throughout dialectical behavior therapy, people develop a range of skills such as core mindfulness, distress tolerance, emotion regulation, and interpersonal effectiveness. These skills help the individual to identify and regulate their emotions, to increase their self-respect, to increase their self-efficacy, and to reduce behaviors such as self-injury [22].

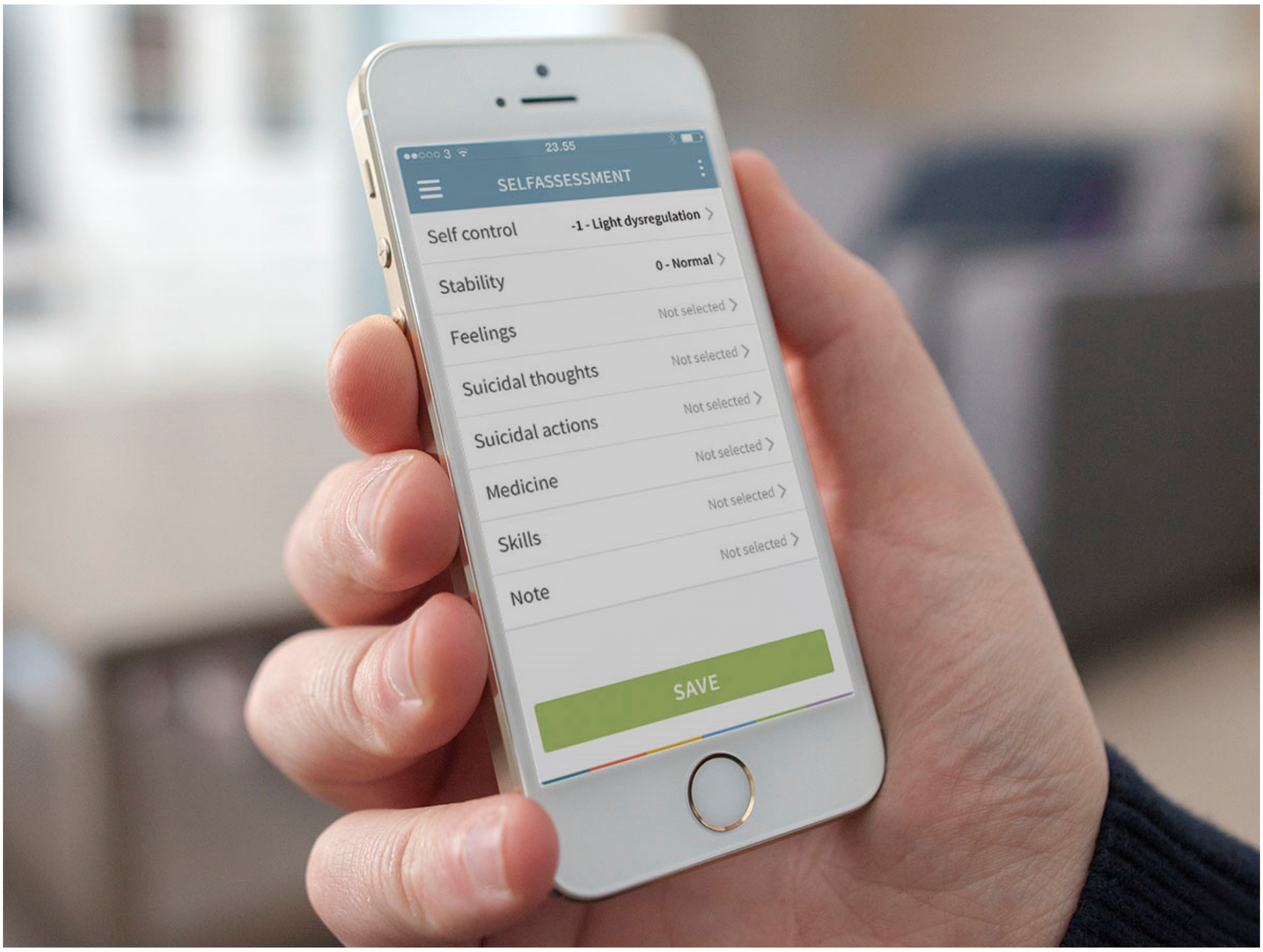
Treatment in this study consisted of groups of 6 to 8 people participating in 20 2-hour group sessions each week. Group sessions combined psychoeducation, skills training, self-reflection, and group discussion. Participants also attended individual sessions with a therapist every fortnight in order to discuss issues and to review progress. An important part of treatment was recording mood and implementing skills (working with relationships, regulating emotions, and building resilience to cope with difficult situations) between weekly sessions.

### Mobile App

The mobile app was developed by a company with extensive experience in the design and implementation of e-health solutions in psychiatry (Monsenso A/S). This organization has conducted clinical trials using mobile apps for both bipolar disorder and depression [23]. The mobile app platform was adapted from earlier research trials. The app was to be used as an alternative to the traditional paper journal used in therapy.

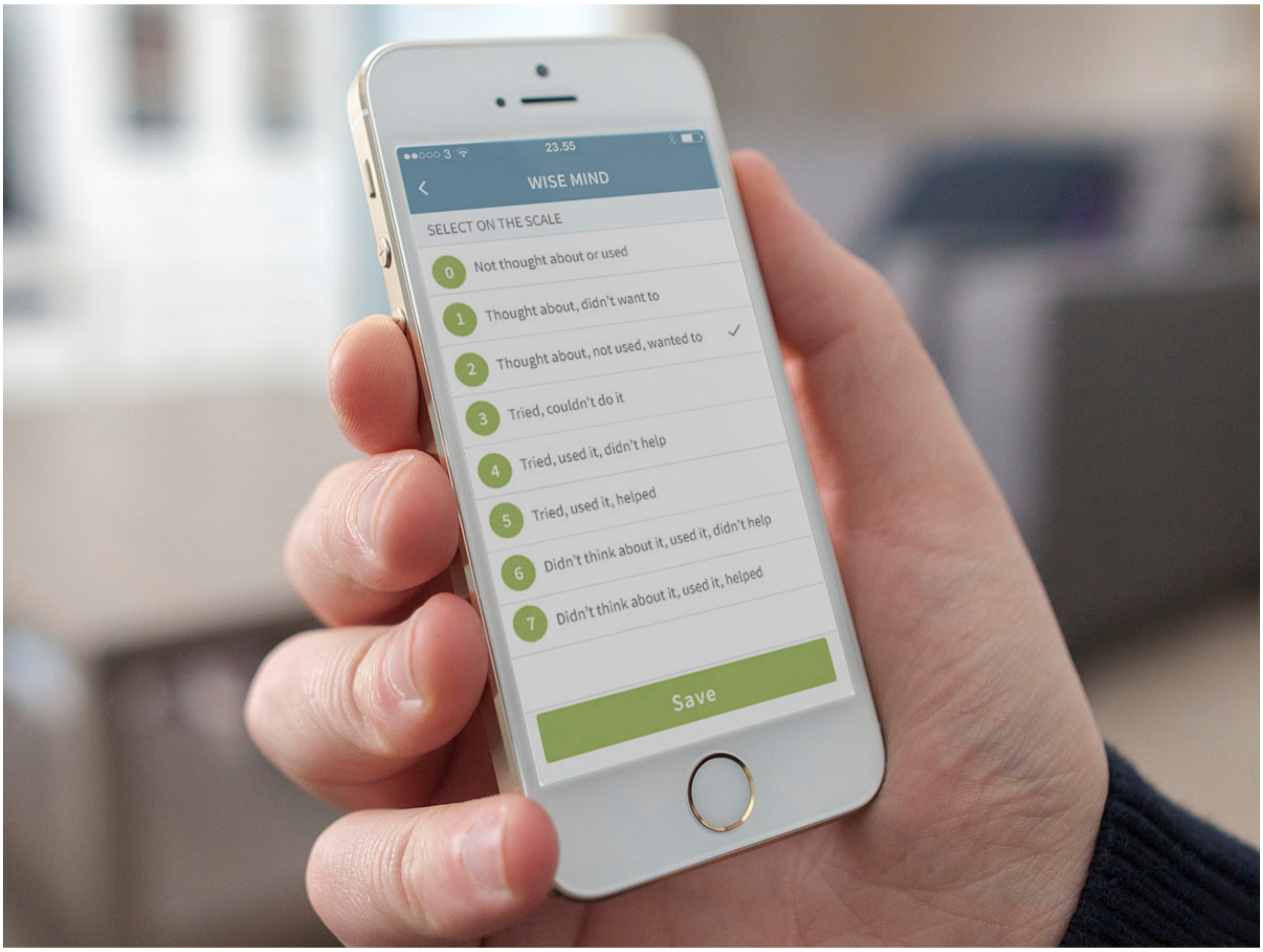
Key elements from dialectical behavior therapy treatment were adapted to the mobile app. These elements included psychoeducation, the recording and monitoring of mood, descriptions and implementation guidelines for a range of cognitive behavioral strategies to deal with challenging situations, and memos where a person could note their experiences *in situ*. The app contained a range of functions that could be accessed by the participant when he or she desired. A Self-Assessment function allowed participants to input information about their mood, behavior, sleep patterns, or any other parameter they wished to monitor (Figure 1). Data were summarized in graphical form and could be accessed using the Visualization function. The Early Warning Signs and Triggers functions allowed the participant to identify and note factors that preceded emotional reactions or inappropriate behaviors. These functions were often used in conjunction with the dialectical behavior therapy Folder function (Figure 2) which contained a range of strategies that could be used when challenges were experienced. The Medicine function allowed participants to create an overview of their medication and to set reminders if they had difficulty with adherence.

**Figure 1.** Self-assessment function menu of the mobile app.



Self control -1 - Light dysregulation
Stability 0 - Normal
Feelings Not selected
Suicidal thoughts Not selected
Suicidal actions Not selected
Medicine Not selected
Skills Not selected
Note

**Figure 2.** Dialectical Behavior Therapy folder function with strategies.



Common aspects of mobile apps such as reminders (push notifications) to complete daily monitoring were also incorporated into the app. App functions were accessible in all situations and the app was used as a support tool outside the therapy sessions.

Information that was input into the app by the participants was saved on a secure server that could be accessed by both the person and their therapist. Information that was input over several days or weeks could be summarized into graphs. These visual summaries could be used to provide an overview of symptom and mood fluctuations over time and to identify specific situations that had been difficult for them for discussion with the therapist in face-to-face appointments; information stored in the app facilitated recall of these situations during therapy sessions.

## Design and Evaluation

The study was an open clinical trial where all participants receiving dialectical behavior therapy group treatment were invited to participate. Participants using the app completed an evaluation questionnaire where they rated their satisfaction with dialectical behavior therapy treatment, alliance with therapist, perceived usefulness of the app, and usage of app between sessions. Responses were rated using a 10-point Likert scale ranging from 1-not at all helpful to 10-extremely helpful or useful.

Descriptive data regarding diagnosis, gender, age, and previous psychiatric treatments were collected. A subset of participants were asked to participate in semistructured interviews where they could describe their experiences using the app; a number of general topics were covered and content was determined by participants. An overview of the topics covered in the semistructured interview and evaluation questionnaire is presented in Textbox 1. Interviews lasted up to one hour, took place at the psychiatric clinic, and were recorded on an iPad. Written and verbal informed consent were obtained from each participant. Two researchers who were experienced psychologists and trained in the use of qualitative methods (SFA and CJP) were responsible for conducting the interviews.

**Textbox 1.** Topics covered in the semistructured interviews and in the evaluation questionnaire. DBT: dialectical behavior therapy.

**Prompts and questions**

Describe your attitudes and use of technology in your daily life.

Describe your experiences in DBT treatment.

Describe your relationship with your therapist.

How (if) has the app been integrated into DBT treatment?

How (if) has the app influenced your relationship with your therapist?

What features of the app (if any) were useful in treatment?

What difficulties (if any) where encountered using the app in treatment?

What improvements (if any) could be made to the app?

Interviews were transcribed verbatim and analyzed using thematic analysis [24], which has been widely used for identifying, analyzing, and reporting patterns (themes) within qualitative data [25]. Two members of the research team (SFA and CJP) independently identified main themes in each interview and met afterward to reach consensus about main themes across all the interviews. Themes that were identified from each of the eight interviews were collapsed into main themes for each topic, and it was noted how many participants endorsed each of these themes. Quotes from participants that illustrate the themes were identified and selected from the interviews. Data from the evaluation questionnaire were summarized using descriptive statistics.

This study used a mixed methods approach, where data from questionnaires (quantitative) and interviews (qualitative) were collected at the same time and then integrated in a concurrent nested design [26]. An emphasis was placed on qualitative information generated from the interviews as this captured user experience more comprehensively, but quantitative data was used in order to contextualize the themes that were identified from the interviews.

### Ethical Considerations

The study was approved by the national association for the storage and analysis of health data (Datatilsynet j.nr. 2008-58-0020 16-000032, REG 135-2016). Written and verbal consent were obtained from all participants involved in the study. Participants were assigned a project number and all information was stored under that number to ensure confidentiality and anonymity.

### Data Management and Storage

Data were stored and handled as confidential information in accordance with Danish legislation for the protection of health data (Datatilsynet j.nr. 2008-58-0020 REG 135-2016). Electronic data were stored on a secure database administered by the Region Zealand Information and Technology department.

## Results

The study consisted of 4 dialectical behavior therapy treatment groups that consecutively trialed the app over a period of 1 year. All participants (N=24) in the treatment groups were asked to complete an evaluation questionnaire and a subset (n=8) were asked to participate in semistructured interviews. Most treatment group participants also participated in the app evaluation (n=20); the participants who did not complete the evaluation questionnaire either could not be contacted (n=2) or did not wish to participate in the evaluation (n=2). The majority of participants were female (female: 19/20, 95%; male: 1/20, 5%). Participants had a mean age of 28.9 (SD 6.7) years and 75% (15/20) had been diagnosed with borderline personality disorder. Table 1 provides a summary of the participant characteristics.

**Table 1.** Characteristics of the participants using the app in dialectical behavior therapy treatment.

| Characteristics of the participants (n=20) | Value |
|---|---|
| Age (years), mean (SD) | 28.9 (6.7) |
| **Gender, n (%)** | |
| Female | 19 (95) |
| Male | 1 (5) |
| **Psychiatric Diagnosis and ICD-10[a], n (%)** | |
| Borderline personality disorder (F60.31) | 15 (75) |
| Mixed personality disorder (DF61.0) | 4 (20) |
| Anxious personality disorder (DF60.6) | 1 (5) |
| **Single or multiple diagnoses** | |
| Single diagnosis | 11 (55) |
| Multiple psychiatric diagnoses (predominantly anxiety, depressive, or personality disorders). | 9 (45) |

[a] ISD-10: International Statistical Classification of Diseases, Tenth Revision.

Table 2 contains a summary of the responses from the evaluation questionnaire. The responses from the questionnaire indicated that participants used the app 20.3 (SD 6.3) weeks during treatment and indicated that participants perceived that treatment was helpful, the alliance with their therapist was strong, the app was helpful during dialectical behavior therapy treatment, and their use of the app between sessions was moderate.

**Table 2.** Participant responses to the evaluation questionnaire about the app.

| Question content | Responses |
|---|---|
| Weeks using app in treatment (weeks) | 20.3 (6.3) |
| How much has dialectical behavior therapy treatment helped (out of 10)[a] | 7.4 (1.6) |
| How useful was the app was in treatment (out of 10) | 7.2 (2.2) |
| How useful was the app in building an alliance with therapist (out of 10) | 7.0 (2.3) |
| How much the app has been used between sessions (out of 10) | 6.9 (2.4) |

[a] Questions were rated on a Likert scale ranging from 1 = not helpful at all to 10 = extremely helpful.

The participants who were interviewed (n=8) were all female (8/8, 100%), most of the women had been diagnosed with borderline personality disorder (6/8, 75%), and more than half (5/8, 63%) had multiple psychiatric diagnoses (other personality disorders, anxiety disorders or ADHD). The majority of women were aged between 25-35 years old and all the women had been in contact with psychiatric services for at least 5 years. Thus, the women interviewed were considered to have complex mental health problems and had received a range of pharmacological and psychosocial interventions prior to participating in dialectical behavior therapy treatment.

Table 3 contains the results from thematic analysis of the qualitative interviews. The main themes that were identified for each topic and representative quotes from participants (quotes that capture the essence of each theme) are presented. The main themes were a positive perception of treatment and therapeutic alliance, and that the app facilitated the access and implementation of relevant dialectical behavior therapy techniques during treatment.

**Table 3.** Common themes and participant quotes from qualitative interviews.

| Topics explored | Main themes (number of themes endorsed) | Participant quotes |
|---|---|---|
| Attitudes toward using technology | Participants were comfortable using technology in all aspects of daily life (7/8)<br>Positive attitudes about using an app in treatment (5/8)<br>Technology needs to be personalized to a person’s needs (3/8) | “It is good idea as I have my mobile with me all the time” (participant 2)<br>“Using a phone is better than paper because it is easier to remember and register” (participant 4) |
| Experience of dialectical behavior therapy treatment | Positive experience (7/8)<br>Treatment provided insight and skills to cope with difficulties (6/8) | “DBT[a] was great, I have learned lots of skills to use in my daily life, I am more calm and I do not have such a bad temperament now” (Participant 4)<br>“ I have learnt about myself and I found out why I act in the way I do and when I feel bad what I can do to make it better” (Participant 5) |
| Relationship with therapist | There was a good relationship where patients felt safe and understood (7/8) | “It (our relationship) has been really good, I have been to many psychologists where I wasn’t understood but I was told there is something wrong with me. But now there was someone who finally understood me and helped me develop another perspective of myself” (participant 4) |
| Experience of using the app in treatment | It was easy to access when needed (5/8) | “It was really good because you are focused in another way. You are more aware what can fool you and how you can use the skills you have learnt (participant 1)<br>“As soon as discover I have used a skill, so could open the app and register it. I didn’t need to remember I had used that skill” (participant 7) |
| Useful parts of app in dialectical behavior therapy treatment | The app was useful in recording mood and use of skills (7/8)<br>The app was useful in recording reflection (5/8) | “I have more awareness of the specific skills that can help me if I am in a situation that is difficult to cope with. If I had an argument with my girlfriend, I could take a break and read in the app what I need here so I don’t switch over to an old response” (participant 1)<br>“I can register my mood, feelings and one has notes where you can write what you have done during the day and remember how you have used the skills and how your mood has been” (participant 6) |
| The use of the app and impact on relationship with therapist | The app provided a common base and promoted collaboration when examining and discussing problematic situations (6/8) | “The app allowed my therapist to follow how I am going and to provide support if required. It provided us with a common overview of what we can examine and discuss together” (participant 6)<br>“The app helped me work better with better with my therapist as she could quickly get insight into how I have been and we had more time to discuss things that were important rather than I have to try and remember the all difficulties I have had” (participant 8) |
| Advantages of using the app in dialectical behavior therapy treatment | The functions of the app were easily accessible (8/8)<br>It helped patients be more aware of treatment issues inside and outside of therapy (5/8)<br>Patients could access skills when they needed them (5/8) | “I am more aware of the skills and it does not require so much effort to take out my mobile phone discretely and use them” (participant 6).<br>“I can see what I have done hangs together with my feelings” (participant 3)<br>“I am aware of what skills I used yesterday and what I should use today” (participant 4) |
| Challenges using the app in treatment | The app should function without major problems and IT[b] support should be available (6/8)<br>There are some technical challenges (2/8) and lacks some flexibility (3/8) | “The scroll function is irritating so it can take a long time to find the part of the app you want” (participant 3)<br>“There are things on the app that are irrelevant” (participant 5)<br>“It can be hard to add your own notes and find them again” (participant 6) |

[a] DBT: dialectical behavior therapy.

[b] IT: information technology.

## Discussion

### Overview

The following study examined user perspectives of incorporating an app into dialectical behavior therapy treatment for personality disorders. Results from the qualitative interviews and quantitative responses indicated that the majority of participants were comfortable with using technology in their daily life, and that they perceived the app as a positive addition to psychotherapy. Dialectical behavior therapy treatment was perceived as a positive experience, and many participants highlighted that they had a good alliance with their treatment provider. Many participants described feeling safe and understood by their therapist. Thus, the context in which the evaluation of the app took place was an environment where participants had a positive attitude toward psychotherapy and technology.

### Ease of Access and Facilitating Psychotherapy

Participant perception of the app based on in-depth interviews was predominantly positive, and they highlighted how the app was a useful tool in recording mood or behavior and for accessing relevant skills to help with difficulties. There was a clear perception that the app facilitated access to many aspects of dialectical behavior therapy both in session and in the real world.

Access to the app was facilitated by the fact that participants always had their phone with them, and that using one's mobile phone in public is perceived as normal. Furthermore, accessing material on the app did not require a change in behavior or require them to remember to take something extra (for example, a manual or notebook). Thus, the incorporation of dialectical behavior therapy material on the mobile phone was built upon existing habits.

The quantitative data from the questionnaires supported this theme of accessibility to relevant information; 75% (14/20) rated the app as very useful in dialectical behavior therapy treatment. Interestingly, while the app was rated as useful, how often (the frequency) participants accessed the app varied greatly. Over half of the participants (12/20, 60%) stated that they accessed the app a lot, but 15% (3/20) stated that they accessed it sometimes, and 25% (5/20) responded that they accessed it a little or not at all. People who did not access the app often between sessions gave a variety of reasons such as they did not have the energy to use the app, they could not see the relevance, or they simply forgot to use it.

This considerable variation in usage despite a positive perception of its usefulness highlights the importance of identifying factors that facilitate or hinder engagement with the app. This issue is particularly important given that engagement in treatment is often linked to effectiveness. A recent review of cognitive behavior therapy interventions using mobile apps also found that despite positive ratings of the usefulness of an app, the ratings did not necessarily reflect longitudinal engagement [24].

### Promotion of Awareness and Reflection

A second prominent theme that was identified from the interviews was that the app helped to increase awareness and to facilitate reflection. This learning and reflection were reinforced during individual sessions where therapists and users would discuss the graphs generated by self-monitoring, and outside the session where the use of push notifications (reminders that were sent via mobile phone) helped users to remember to record their mood and activities. Regularly recording mood and reviewing the results generated by the app with the therapist was perceived as useful and to support the core components of dialectical behavior therapy treatment.

This theme of the app being a useful tool in therapy was supported by the quantitative data where 70% (14/20) of participants rated the app as very to extremely useful in treatment and only one person rated the app as not useful at all.

### Building Therapeutic Alliance

None of the participants perceived the app as having a negative impact on the therapeutic relationship, in contrast to the concern that technology may disrupt the therapeutic process. A key theme identified from the interviews was that the use of the app was actually perceived to promote better collaboration between therapist and patient as users stated that it provided a common source of information which could be used for in-depth discussion.

Results from the questionnaires also supported the theme of strengthening therapeutic alliance; 80% (16/20) felt it contributed to building a good therapeutic alliance and only 10% (2/20) of participants felt it contributed very little or nothing at all to the therapeutic relationship.

Furthermore, dropout rates from this intervention were under 10% which is significantly less than what is expected for dialectical behavior therapy treatment within this population. While the study design prohibits the conclusion that integration of the app into dialectical behavior therapy treatment reduces dropout rates, it does not appear that integration of an app into dialectical behavior therapy treatment was associated with higher dropout rates.

### Technical Problems Can Result in Disengagement

Overall, participants were accepting of and comfortable with integrating this mobile technology in their therapy and relatively few disadvantages were identified. One participant highlighted a technical problem regarding the app where it would freeze when updating. This technical problem resulted in that participant not using the app until the problem was rectified. Several other participants commented on the importance of the app functioning reliably and smoothly, and that technical support should be readily available to quickly solve any problems that arise.

The app functions that were most used by participants were self-assessment, visualization, and the therapy folder with strategies. General factors that influenced the frequency of use of different functions were the perceived relevance of the function, active use of the function during individual sessions, and ease of use. Interestingly, a number of people noted their desire to use the app varied depending on their mood where low mood was associated with reduced use. A couple of people commented that their motivation to use the app deceased over time as they became familiar with its content.

None of the participants who were interviewed identified any negative or harmful effects of using the app, but one person did have general concerns about other people potentially accessing or using personal data from the app. Overall, participants were confident in the security of the data stored in the app, but they were concerned that information could be accessed by people other than those to whom they had given specific permission to (such as the treating clinician). This perception of data security was as a consequence of the highly personal nature of some of the reflections stored in the memo function.

### Personalizing Functions May Increase Engagement

There were several suggestions to improve the app; the most common was adaptation of the scroll function so the app could remember where the user was when last accessing or registering information. Another suggestion was to increase the flexibility of the app by being able to personalize different functions (for example, to be able to switch off some functions and to expand others for streamlined access to the most frequently used functions).

Finally, a subgroup of participants who had previously used the written dialectical behavior therapy workbook (n=6) were asked to reflect about using the app compared to the written manual. The majority of this group (5/6, 83%) preferred using the app over using the paper manual; they highlighted advantages of the app such as portability, ease of access, and less chance of losing information or worksheets. One participant suggested that having both electronic and paper formats could be helpful depending on the context. For example, this person preferred using the paper manual when at home so they had access detailed information and preferred using the app when not at home as it was more portable and convenient.

### Participant Engagement is Only Half the Picture in Successful Implementation

While this study focused on user perspectives, it is important to acknowledge the system in which the app was implemented. The app was seen as a support tool for psychotherapy, and therefore, the clinical staff also played an important role in the integration of the mobile app into treatment. Staff were responsible for introducing and teaching participants about app functions, following up on data input by the participants, and incorporating output from the app (for example, graphs, summaries, and notes from participants) into therapy sessions. Focus group interviews with clinical staff were conducted to capture their perspectives as another part of the evaluation. Staff highlighted the importance of receiving adequate training and ongoing support throughout treatment so that they were comfortable using the app with their clients. Furthermore, staff stated there was the need for sufficient time to learn and integrate the app meaningfully into clinical treatment. This meant personnel needed to have a reduced caseload while learning and integrating the app, thus support and approval from their line managers was required.

### Study Limitations

The study had a number of limitations. First, results were based on a small sample of participants which is a common feature of qualitative studies. As a result, it may be difficult to generalize the findings to all people who receive dialectical behavior therapy interventions for personality disorders. Second, the study focuses on participant perception of the experience of using the app; therefore, findings may not reflect actual behavior. Future studies should incorporate sensor data and daily monitoring information from the app to quantify actual usage. This function was not available in this version of the app. Finally, no information regarding symptoms, behavioral change (for example, self-harm), or measurement of therapeutic alliance was systematically collected in this study. Thus, it was not possible to determine if using the app affected dialectical behavior therapy treatment effectiveness. Future studies could determine the efficacy of integrating an app into dialectical behavior therapy using suitable study design.

## Conclusions

Our study investigated participant experience of the integration of a mobile app into dialectical behavior therapy treatment for personality disorders. Participants had a positive attitude toward the use of technology and perceived dialectical behavior therapy treatment as useful in treating their mental health difficulties.

Qualitative and quantitative results indicated that the app was widely accepted and used in treatment by participants. Participants described that the content of the app was easily accessible and often helped to facilitate self-monitoring and the use of strategies and reflection techniques that were learned in therapy sessions in the real world. While the app was seen as a useful addition to treatment, usage of the app between sessions varied indicating that engagement fluctuated. Given the link between engagement and positive outcomes, further research into factors that affect engagement with technology is needed. There were relatively few disadvantages identified by users although there were some suggestions to improve the design of the app to increase its flexibility; this suggests personalized app functions may warrant further exploration. The positive findings from this study are in line with a recent review [27] that highlighted the feasibility and acceptability of integrating technology into clinical treatments for serious mental illness.

It is important to acknowledge that this evaluation does not provide information on whether the integration of an app into dialectical behavior therapy treatment had a positive effect on treatment outcomes. The results suggest that an app could have benefits and that further evaluation is warranted. Researchers and clinicians should continue to collaborate with psychiatric service users in to understand how technology can be meaningfully integrated into psychotherapy in order to promote engagement and to improve treatment outcomes.

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## Authors' Contributions

SFA, JEJ, and ES designed the study. CJP and SFA performed the interviews and thematic analysis. RJ and CJP were therapists in the study. SFA wrote the first draft of the paper and all authors reviewed and proofread the manuscript in its final version.

## Conflicts of Interest

None declared.

## References

1. Stoffers JM, Völlm BA, Rücker G, Timmer A, Huband N, Lieb K. Psychological therapies for people with borderline personality disorder. Cochrane Database Syst Rev 2012 Aug 15(8):CD005652. [doi: 10.1002/14651858.CD005652.pub2] [Medline: 22895952]
2. Stoffers JM, Völlm BA, Rücker G, Timmer A, Huband N, Lieb K. Psychological therapies for people with borderline personality disorder. Cochrane Database Syst Rev 2012 Aug 15(8):CD005652. [doi: 10.1002/14651858.CD005652.pub2] [Medline: 22895952]
3. Cristea IA, Gentili C, Cotet CD, Palomba D, Barbui C, Cuijpers P. Efficacy of psychotherapies for borderline personality disorder: a systematic review and meta-analysis. JAMA Psychiatry 2017 Apr 01;74(4):319-328. [doi: 10.1001/jamapsychiatry.2016.4287] [Medline: 28249086]
4. McLaughlin SPB, Barkowski S, Burlingame GM, Strauss B, Rosendahl J. Group psychotherapy for borderline personality disorder: a meta-analysis of randomized-controlled trials. Psychotherapy (Chic) 2019 Jun;56(2):260-273. [doi: 10.1037/pst0000211] [Medline: 30869973]
5. Oud M, Arntz A, Hermens ML, Verhoef R, Kendall T. Specialized psychotherapies for adults with borderline personality disorder: a systematic review and meta-analysis. Aust N Z J Psychiatry 2018 Oct;52(10):949-961 [FREE Full text] [doi: 10.1177/0004867418791257] [Medline: 30091375]
6. Kliem S, Kröger C, Kosfelder J. Dialectical behavior therapy for borderline personality disorder: a meta-analysis using mixed-effects modeling. J Consult Clin Psychol 2010 Dec;78(6):936-951. [doi: 10.1037/a0021015] [Medline: 21114345]
7. Panos PT, Jackson JW, Hasan O, Panos A. Meta-analysis and systematic review assessing the efficacy of dialectical behavior therapy (DBT). Research on Social Work Practice 2013 Sep 19;24(2):213-223. [doi: 10.1177/1049731513503047]
8. Hermens MLM, van Splunteren PT, van den Bosch A, Verheul R. Barriers to implementing the clinical guideline on borderline personality disorder in the Netherlands. Psychiatr Serv 2011 Nov;62(11):1381-1383. [doi: 10.1176/ps.62.11.pss6211_1381] [Medline: 22211222]
9. Stiglmayr C, Stecher-Mohr J, Wagner T, Meiβner J, Spretz D, Steffens C, et al. Effectiveness of dialectic behavioral therapy in routine outpatient care: the Berlin Borderline Study. Borderline Personal Disord Emot Dysregul 2014;1:20 [FREE Full text] [doi: 10.1186/2051-6673-1-20] [Medline: 26401303]
10. Barnicot K, Katsakou C, Marougka S, Priebe S. Treatment completion in psychotherapy for borderline personality disorder: a systematic review and meta-analysis. Acta Psychiatr Scand 2011 May;123(5):327-338. [doi: 10.1111/j.1600-0447.2010.01652.x] [Medline: 21166785]
11. Lindhiem O, Bennett CB, Rosen D, Silk J. Mobile technology boosts the effectiveness of psychotherapy and behavioral interventions. Behav Modif 2015 Jul 17;39(6):785-804. [doi: 10.1177/0145445515595198]
12. Cuijpers P, van Straten A, Andersson G. Internet-administered cognitive behavior therapy for health problems: a systematic review. J Behav Med 2008 Apr;31(2):169-177 [FREE Full text] [doi: 10.1007/s10865-007-9144-1] [Medline: 18165893]
13. Cuijpers P, van STraten A, Warmerdam L, van Rooy MJ. Recruiting participants for interventions to prevent the onset of depressive disorders: possible ways to increase participation rates. BMC Health Serv Res 2010;10:181 [FREE Full text] [doi: 10.1186/1472-6963-10-181] [Medline: 20579332]
14. Torous J, Firth J, Mueller N, Onnela JP, Baker JT. Methodology and reporting of mobile heath and smartphone application studies for schizophrenia. Harv Rev Psychiatry 2017;25(3):146-154 [FREE Full text] [doi: 10.1097/HRP.0000000000000133] [Medline: 28234658]
15. Torous J, Nicholas J, Larsen ME, Firth J, Christensen H. Clinical review of user engagement with mental health smartphone apps: evidence, theory and improvements. Evid Based Ment Health 2018 Jun 05. [doi: 10.1136/eb-2018-102891] [Medline: 29871870]
16. Martínez-Pérez B, de la Torre-Díez I, López-Coronado M. Privacy and security in mobile health apps: a review and recommendations. J Med Syst 2015 Jan;39(1):181. [doi: 10.1007/s10916-014-0181-3] [Medline: 25486895]
17. Barnicot K, Gonzalez R, McCabe R, Priebe S. Skills use and common treatment processes in dialectical behaviour therapy for borderline personality disorder. J Behav Ther Exp Psychiatry 2016 Sep;52:147-156. [doi: 10.1016/j.jbtep.2016.04.006] [Medline: 27132175]
18. Prada P, Zamberg I, Bouillault G, Jimenez N, Zimmermann J, Hasler R, et al. EMOTEO: A smartphone application for monitoring and reducing aversive tension in borderline personality disorder patients, a pilot study. Perspect Psychiatr Care 2017 Oct;53(4):289-298. [doi: 10.1111/ppc.12178] [Medline: 27439663]

19. Rizvi SL, Dimeff LA, Skutch J, Carroll D, Linehan MM. A pilot study of the DBT coach: an interactive mobile phone application for individuals with borderline personality disorder and substance use disorder. Behav Ther 2011 Dec;42(4):589-600. [doi: 10.1016/j.beth.2011.01.003] [Medline: 22035988]
20. Rizvi SL, Hughes CD, Thomas MC. The DBT Coach mobile application as an adjunct to treatment for suicidal and self-injuring individuals with borderline personality disorder: a preliminary evaluation and challenges to client utilization. Psychol Serv 2016 Nov;13(4):380-388. [doi: 10.1037/ser0000100] [Medline: 27797571]
21. Habermeyer E, Habermeyer V, Jähn K, Domes G, Nagel E, Herpertz SC. [An internet based discussion board for persons with borderline personality disorders moderated health care professionals]. Psychiatr Prax 2009 Jan;36(1):23-29. [doi: 10.1055/s-2008-1067508] [Medline: 18777461]
22. O'Connell B, Dowling M. Dialectical behaviour therapy (DBT) in the treatment of borderline personality disorder. J Psychiatr Ment Health Nurs 2014 Aug;21(6):518-525. [doi: 10.1111/jpm.12116] [Medline: 24191948]
23. Faurholt-Jepsen M, Torri E, Cobo J, Yazdanyar D, Palao D, Cardoner N, et al. Smartphone-based self-monitoring in bipolar disorder: evaluation of usability and feasibility of two systems. Int J Bipolar Disord 2019 Jan 04;7(1):1 [FREE Full text] [doi: 10.1186/s40345-018-0134-8] [Medline: 30610400]
24. Rathbone AL, Clarry L, Prescott J. Assessing the efficacy of mobile health apps using the basic principles of cognitive behavioral therapy: systematic review. J Med Internet Res 2017 Nov 28;19(11):e399 [FREE Full text] [doi: 10.2196/jmir.8598] [Medline: 29187342]
25. Braun V, Clarke V. Using thematic analysis in psychology. Qualitative Research in Psychology 2006 Jan;3(2):77-101. [doi: 10.1191/1478088706qp063oa]
26. Halcomb E, Hickman L. Mixed methods research. Nurs Stand 2015 Apr 08;29(32):41-47. [doi: 10.7748/ns.29.32.41.e8858] [Medline: 25850508]
27. Naslund JA, Marsch LA, McHugo GJ, Bartels SJ. Emerging mHealth and eHealth interventions for serious mental illness: a review of the literature. J Ment Health 2015 Aug 19:1-12. [doi: 10.3109/09638237.2015.1019054] [Medline: 26017625]

## Abbreviations

**DBT:** dialectical behavior therapy
**ICD-10:** International Statistical Classification of Diseases, Tenth Revision
**IT:** information technology

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Original Paper

# Flattening the Mental Health Curve: COVID-19 Stay-at-Home Orders Are Associated With Alterations in Mental Health Search Behavior in the United States

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## Abstract

**Background:** The coronavirus disease (COVID-19) has led to dramatic changes worldwide in people's everyday lives. To combat the pandemic, many governments have implemented social distancing, quarantine, and stay-at-home orders. There is limited research on the impact of such extreme measures on mental health.

**Objective:** The goal of this study was to examine whether stay-at-home orders produced differential changes in mental health symptoms using internet search queries on a national scale.

**Methods:** In the United States, individual states vary in their adoption of measures to reduce the spread of COVID-19; as of March 23, 2020, 11 of the 50 states had issued stay-at-home orders. The staggered rollout of stay-at-home measures across the United States allows us to investigate whether these measures impact mental health by exploring variations in mental health search queries across the states. This paper examines the changes in mental health search queries on Google between March 16-23, 2020, across each state and Washington, DC. Specifically, this paper examines differential changes in mental health searches based on patterns of search activity following issuance of stay-at-home orders in these states compared to all other states. The participants were all the people who searched mental health terms in Google between March 16-23. Between March 16-23, 11 states underwent stay-at-home orders to prevent the transmission of COVID-19. Outcomes included search terms measuring anxiety, depression, obsessive-compulsive, negative thoughts, irritability, fatigue, anhedonia, concentration, insomnia, and suicidal ideation.

**Results:** Analyzing over 10 million search queries using generalized additive mixed models, the results suggested that the implementation of stay-at-home orders are associated with a significant flattening of the curve for searches for suicidal ideation, anxiety, negative thoughts, and sleep disturbances, with the most prominent flattening associated with suicidal ideation and anxiety.

**Conclusions:** These results suggest that, despite decreased social contact, mental health search queries increased rapidly prior to the issuance of stay-at-home orders, and these changes dissipated following the announcement and enactment of these orders. Although more research is needed to examine sustained effects, these results suggest mental health symptoms were associated with an immediate leveling off following the issuance of stay-at-home orders.

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**KEYWORDS**

COVID-19; coronavirus; stay-at-home orders; mental health; suicide; anxiety; infodemiology; infoveillance; search trends; health information needs

## Introduction

The 2019 novel coronavirus disease (COVID-19), a symptomatically broad disease transmitted by human-to-human droplets or direct contact, has been declared by the World Health Organization to be an international crisis [1,2]. The rapid, largely uncontrolled spread of COVID-19 has impacted every facet of American life, calling for dramatic shifts in the social and professional behavior of nearly 327 million people.

In the early phase of an outbreak, reducing physical distance and interactions between individuals in a population is an effective way of stopping or limiting disease spread [3]. In early February 2020, the Centers for Disease Control and Prevention recommended social distancing across the United States as a strategy to prevent the rapid spread of COVID-19 and subsequent overburdening of the health care system [4]. Despite these and other measures, there has been an exponential spread of COVID-19. During this time, a simulation model suggested that only the most stringent social distancing interventions would be effective at reducing the spread [5]. In the absence of federal guidance, individual states have enacted varying degrees of these recommendations. Such enactment has manifested in the closure of schools and nonessential businesses and, more recently, in the issuance of shelter-in-place notices and stay-at-home orders in several states (hereafter referred to as stay-at-home orders). Stay-at-home orders reflect the most disruptive measure, resulting in a mass quarantine that restricts individuals to their place of residence except for essential travel. As of March 23, 2020, the following 11 states have issued these orders: California, Connecticut, Delaware, Illinois, Louisiana, Massachusetts, Michigan, New Jersey, New York, Ohio, and West Virginia. Of these 11 states to announce stay-at-home orders due to COVID-19, the stay-at-home orders for California, New Jersey, New York, Illinois, and Washington had taken effect as of March 23.

Although social distancing measures are necessary to protect physical health, less is known about the impact of such measures on mental health. A rapid review of the psychological impact of quarantine found that such measures were associated with high levels of psychological distress including posttraumatic stress symptoms, confusion and anger, and high prevalence of low mood and irritability [6]. The authors note that a lack of clear communication from governments to their citizens may heighten uncertainty, which could be a key driver of distress. This suggests that clear governmental action may reduce psychological distress. Nevertheless, none of the included studies in the rapid review assessed psychological distress immediately pre- and postenactment of a quarantine. Consequently, longitudinal data regarding the potential changes of mental health symptoms immediately before and after implementations of stay-at-home orders is needed.

To date, many studies across the world have employed internet search trends to study epidemiological changes in mental health [7-14]. Nearly all of these published studies have found an association between internet search behavior and real-world mental health data, although the magnitude of this effect has differed across studies. Specifically, studies have found robust associations between suicide search queries and completed suicide rates [7,10,12] with extremely high interrater reliability (intraclass correlation coefficient [ICC]=0.98) between searches using the term "suicides" and observed suicide rates [15]. Many of these studies have also found links between mental health search data and observed rates of life stressors, such as divorce and unemployment [7,10,12]. These findings provide support for using mental health queries as effective proxies for real world mental health outcomes. They in effect "bridge the gap" between internet search trends and epidemiological data, allowing for important public health application to this large corpus of readily available and easily accessible data.

This paper evaluated the impact of stay-at-home orders on mental health search queries between March 16-23, 2020. This work used Google Trends to quantify changes in search behavior in the 50 states within the United States as well as the District of Columbia (Washington, DC) with the goal of better understanding the acute mental health impact of stay-at-home orders amid COVID-19. Specifically, we sought to determine whether stay-at-home orders were associated with increased affective symptoms as might be suggested by theories related to potential impacts of prolonged social isolation, or, in contrast, whether there might be improved mental health from clear government action rather than continuing to live in a state of uncertainty caused by government inaction [16,17]. We investigated the following research questions:

1. Would stay-at-home orders significantly alter the trajectory of mental health search queries across time between March 16-23, 2020, in the United States, compared to states that had not yet enacted stay-at-home orders?
2. Would the effects of stay-at-home orders on search queries be isolated to specific symptom domains (eg, anxiety, depression, suicide) or be consistent across symptom domains?
3. Would the results of stay-at-home orders uniquely impact search queries related to mental health symptoms or be consistent with queries on physical health symptoms (both related and unrelated to COVID-19)?

## Methods

### Google Trends

Google is the leading search engine, retaining a dominant market share of all search traffic within the United States and worldwide. Google Trends uses large-scale search volume and allows users to download information about search volume for a given time and place. Google Trends is posted publicly, and data can be downloaded directly through Google's web portals or through freely available software [18]. Google Trends normalizes search data per search locale (in this case, per state). Normalization occurs using the following process: each data point is divided by the total search volume of the geography and time range it represents to compare relative popularity; the results are then scaled on a range of 0-100 based on a topic's proportion to all searches on all topics. Such normalization has the effect of controlling for the total volume of internet use across time. We used these normalized values as the outcome; a positive upward trajectory of a given search term means that term increased in relative frequency compared to other terms. The data was obtained for each hour between 11 PM on March 16, 2020, and 10 PM on March 23, 2020, EST. This period was chosen because we wanted to investigate the immediate time trends before and after issuance and implementation of stay-at-home orders. Orders were announced and implemented for 11 states within this period of time. We did not examine data prior to March 16 because Google Trends only reports hourly data for up to 7 days prior. See Figure 1 and Table 1 for a study timeline.

**Figure 1.** Timeline of stay-at-home order policy announcement (red) and implementation (blue).

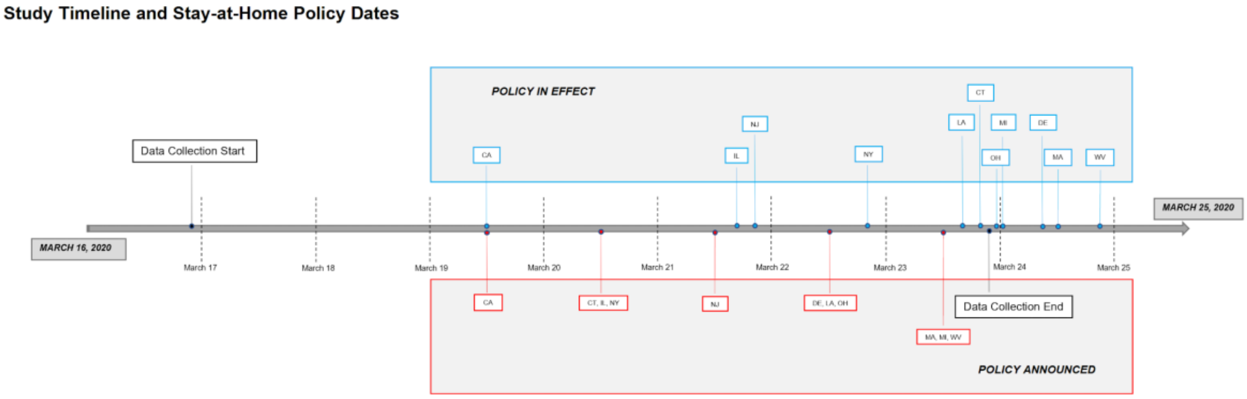


**Table 1.** States with stay-at-home orders as of the date of data collection.[a]

| State | Policy announcement date | Policy effect date | Day difference (rounded) | Cumulative state incidence (cases), n[b] | Estimated IR[c] (per 100,000 people)[d] |
|---|---|---|---|---|---|
| California | Thursday, March 19 | Thursday, March 19 | 0 | 2267 | 5.7 |
| Connecticut | Friday, March 20 | Monday, March 23, 8 PM | 3 | 415 | 11.6 |
| Delaware | Sunday, March 22 | Tuesday, March 24, 8 AM | 2 | 87 | 8.9 |
| Illinois | Friday, March 20 | Saturday, March 21, 5 PM | 1 | 1285 | 10.2 |
| Louisiana | Sunday, March 22 | Monday, March 23, 5 PM | 1 | 1210 | 26.0 |
| Massachusetts | Monday, March 23 | Tuesday, March 24, noon | 1 | 777 | 11.1 |
| Michigan | Monday, March 23 | Tuesday, March 24, 12:01 AM | 1 | 1335 | 13.3 |
| New Jersey | Saturday, March 21 | Saturday, March 21, 9 PM | 0 | 2844 | 31.8 |
| New York | Friday, March 20 | Sunday, March 22, 8 PM | 2 | 25,665 | 132.0 |
| Ohio | Sunday, March 22 | Monday, March 23, 11:59 PM | 1 | 443 | 3.8 |
| West Virginia | Monday, March 23 | Tuesday, March 24, 8 PM | 1 | 22 | 1.2 |

[a] All data represented as of March 24, 2020. Policy dates were taken from examination of state news reporting as well as local government websites.

[b] Cumulative incidence (total cases) as of March 24, 2020, 1:14 PM EST [19].

[c] IR: infection rate.

[d] Total state population based on 2020 census records.

## Search Terms

### *Mental Health*

We used the following search terms to examine common mental health symptoms: "anxiety," "depression," "OCD" (obsessive-compulsive disorder), "hopeless," "angry," "afraid," "apathy," "worthless," "worried," "restless," "irritable," "tense," "scattered," "tired," "avoiding," "procrastinate," "insomnia," "suicidal," and "suicide." These mental health terms were validated by prior research on mental health using Google Trends [20]. We also adapted other terms that measure

Diagnostic and Statistical Manual of Mental Disorders, 5th edition affective disorder symptoms based on prior research assessing rapid affective symptom changes, including single-items to assess anxiety (both in terms of subjective thoughts, including fear, tense, and restless, as well as avoidance behaviors, including avoiding and procrastination), negative thoughts (hopeless, worried), irritability (anger, irritable), fatigue (tired), anhedonia (apathy), diminished ability to think or concentrate (scattered), disturbed sleep (insomnia), and suicidal ideation (suicidal, suicide) [21,22].

### *Physical Health Terms Unrelated to Known COVID-19 Symptoms*

To determine whether changes in search trends were specific to searches related to mental health, we contrasted mental health symptoms to physical health symptoms that have no current known association with COVID-19. The physical health searches included: "abrasion," "allergic," "angina," "apnea," "bleeding," "blister," "bruising," "conjunctivitis," "constipation," "discharge," "earache," "flatulence," "fracture," "hemorrhage," "incontinence," "inflammation," "itching," "lesions," "rash," "spasms," "swelling," and "syncope." These terms were used as prespecified falsification hypotheses to provide useful control conditions to further ensure that conclusions drawn were not an artifact of the methodology alone [23].

### *Physical Health Terms Related to Known COVID-19 Symptoms*

We also examined search queries for COVID-19 physical health symptoms to determine whether the changes in mental health symptoms related to stay-at-home orders were distinct from changes in COVID-19 physical health symptoms. Consequently, we also conducted searches on physical health terms among known symptoms of COVID-19 including "bloating," "blurry," "congestion," "cough," "coughing," "croup," "diarrhea," "dizzy," "fainting," "fever," "pain," "sneezing," "strep," "stuffy," and "vomiting."

## Analyses

The goal of the present analyses was to investigate change in search trends across time. Consequently, it was important to account for potentially nonlinear trends across time and account for interdependence of observations. As such, the current analyses used generalized additive mixed models (GAMMs). GAMMs combine the features of models that allow predictors to have a highly flexible relationship with the outcome so long as the relationship has a smooth functional form (ie, is continuous and differentiable) such as enabled by thin plate regression splines and multilevel models that account for the lack of statistical independence in the observations made on the same units across time (see [24] for a review). Splines within GAMMs were used as they allow the data to take on any smooth functional form, but the models only allow nonlinearity in the predictor-outcome relationship if nonlinearity would provide the best fit to the data. We chose these methods over more popular but less flexible approaches (eg, higher-order polynomial transformations) because thin plate regression splines better address the issue of number and location of the knots. In particular, we made use of thin plate regression splines that use an eigenvalue decomposition to pick the basis coefficients that can explain the greatest variance. This is advantageous as it does not require a researcher to choose knot locations, thereby reducing subjectivity in modeling and otherwise having optimal bases [25], and better accommodating a higher number of predictors [26]. Notably, thin plate regression splines have been shown to not overfit the data in the way that other spline methods may [27].

We used the following model for each respective outcome:

$$\text{Outcome}_{i,j} \sim s_1(\text{Time}_{i,j}) + s_2(\text{TimeSincePolicy}_{i,j}) * \text{StayAtHomePolicy}_{\text{i,j}} + u_{1,i} + s_{3,i}(\text{Time}_{i,j}) \quad \mathbf{(1)}$$

Outcome represents each respective search term for state *i* at time *j*; Time represents the number of hours since 11 PM on March 16, 2020; TimeSincePolicy represents a time difference variable between the observed time and when the implementation of the stay-at-home policy began (defined to be 0 if the policy had not been enacted); StayAtHomePolicy represents a dummy variable representing 0 for when the policy was not in place and 1 when the policy was in place. The terms represent a smooth, thin plate regression spline, wherein the term is allowed to have a linear or nonlinear relationship with the outcome. However, nonlinearity is penalized such that data will only become nonlinear if it results in a substantially greater model fit. Note that $u_1$ and $s_3$ represent random effects, with $u_1$ representing a vector of random intercepts of state and $s_3$ representing a vector of random smooth slopes of the time trend for each state (thus allowing a nonlinear random effect to account for changes in each state). The default *k* (10) in *mgcv* value was chosen for all analyses to balance smooth fitting with computational time (as allowing a smooth spline for each random effect is computationally expensive) [28]. The latter seeks to estimate the search trajectory trend that would have occurred for that state in the absence of it implementing a stay-at-home policy. Thus, the primary term of interest is $s_2$, which estimates the effects of the stay-at-home policy intervention as a deviation from the state-specific counterfactual trend that would have occurred had there not been a stay-at-home order issued.

## Ethics

This paper was not considered human subjects research because it used publicly available data, and as such was exempt from human subject approval.

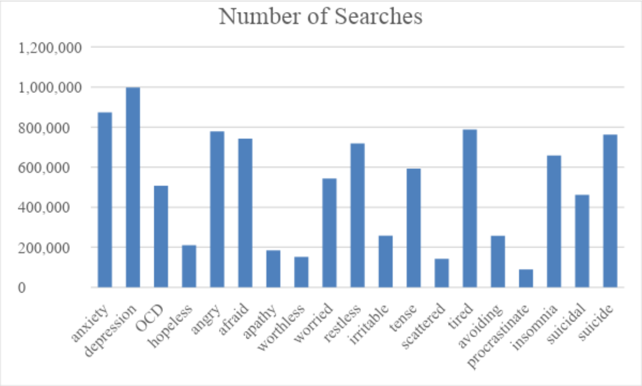
# Results

### Volume of Mental Health Search Queries Across the United States

We estimated the total volume of search queries related to mental health by comparing and using a reported value of search terms from the Google Trends trending terms in the United States for a given day, multiplying the normalized value of each mental health term, and then dividing by the comparison term with the known absolute increase value noted across the United States. Based on this method, there were a total of 9,717,876 total searches on mental health from March 18 through March

23, 2020, (we only calculated the total search volume beginning on March 18 rather than March 16 as we were not aware of the absolute search volume terms being reported until March 25; the hour-to-hour measures reported in Google Trends only goes back a total of 7 days). See Figure 2 for a breakdown of searches per search term. Based on the average number of searches per day between March 18-23, we estimated that approximately 13 million mental health search queries were conducted between March 16-23.

**Figure 2.** This plot depicts the estimated total volume of searches between March 18-23, 2020, for each search term. OCD: obsessive-compulsive disorder.



## Mental Health Symptom Searches and Stay-at-Home Orders

We found a significant association between queries involving 14 (of 19 total) mental health search terms and implementation of stay-at-home orders (see Table 2 for a summary). Our results showed nonlinear changes in 12 of these mental health symptoms over time associated with the announcement of stay-at-home orders. In particular, “afraid,” “anxiety,” “apathy,” “avoiding,” “hopeless,” “insomnia,” “irritable,” “procrastinate,” “restless,” “suicide,” “suicidality,” and “worthless” each showed rapid increases in search queries several days prior to the official enactment of the stay-at-home policies (see Figures 3 and 4 and Supplementary Figures A1-A3 in Multimedia Appendix 1). Moreover, each of these terms was associated with a leveling-off effect approximately 2 days prior to the implementation of the stay-at-home policy (ie, approximately the same time as the stay-at-home policy was announced). For all but 1 of these 12 symptoms (ie, “avoiding”), the leveling off remained consistent through the last day of data collection. Note that the terms associated with the strongest changes in these trends were “afraid,” “suicide,” “anxiety,” and “suicidal” (see Figure 2).

**Table 2.** Changes in search behavior related to stay-at-home orders.[a]

| Search term | EDF[b] | Ref.df[c] | *F* | *P* value[d] |
|---|---|---|---|---|
| Anxiety | 3.969 | 3.999 | 12.846 | <.001 |
| Depression | 1.788 | 2.073 | 2.765 | .06 |
| OCD[e] | 1.000 | 1.000 | 0.189 | .66 |
| Hopeless | 3.791 | 3.955 | 14.519 | <.001 |
| Angry | 2.612 | 2.830 | 1.775 | .19 |
| Afraid | 4.000 | 4.000 | 16.192 | <.001 |
| Apathy | 1.000 | 1.000 | 23.870 | <.001 |
| Worthless | 3.888 | 3.985 | 4.349 | .002 |
| Worried | 1.000 | 1.000 | 1.292 | .26 |
| Restless | 3.905 | 3.985 | 4.314 | .002 |
| Irritable | 3.450 | 3.687 | 4.108 | .002 |
| Tense | 1.000 | 1.000 | 0.399 | .53 |
| Scattered | 1.046 | 1.077 | 16.123 | <.001 |
| Tired | 1.000 | 1.000 | 9.113 | .003 |
| Avoiding | 2.672 | 2.865 | 5.301 | <.001 |
| Procrastinate | 1.556 | 1.800 | 7.057 | .005 |
| Insomnia | 3.916 | 3.993 | 10.209 | <.001 |
| Suicidal | 3.970 | 3.999 | 13.446 | <.001 |
| Suicide | 3.996 | 4.000 | 20.314 | <.001 |

[a] This table corresponds to the test of the term $s_2$ in the model.

[b] EDF stands for the model estimated residual degrees of freedom, where 1 corresponds to a linear deviation from the time trend.

[c] Ref.df refers to the number of model data minus the model degrees of freedom.

[d] Significant values represent the difference between what would have happened in a state with a stay-at-home policy intervention and what would have happened in the absence of that intervention.

[e] OCD: obsessive-compulsive disorder.

**Figure 3.** This plot depicts the changes in search patterns relative to the orders going into effect. Negative time of stay-at-home values reflects the time before the stay-at-home orders go into effect, and positive values reflect the time following the order going into effect. Note that in this plot, the predictions are not normalized to show the magnitude of the effects. The centering performed here subtracts the actual value at 0 from the estimates of this term. The escalation phase designates approximately 4 days prior to the stay-at-home orders going into effect. The interruption phase spans between approximately 4 days and 0 days before the orders go into effect, and the new normal phase represents the times the 5 days after orders go into effect.

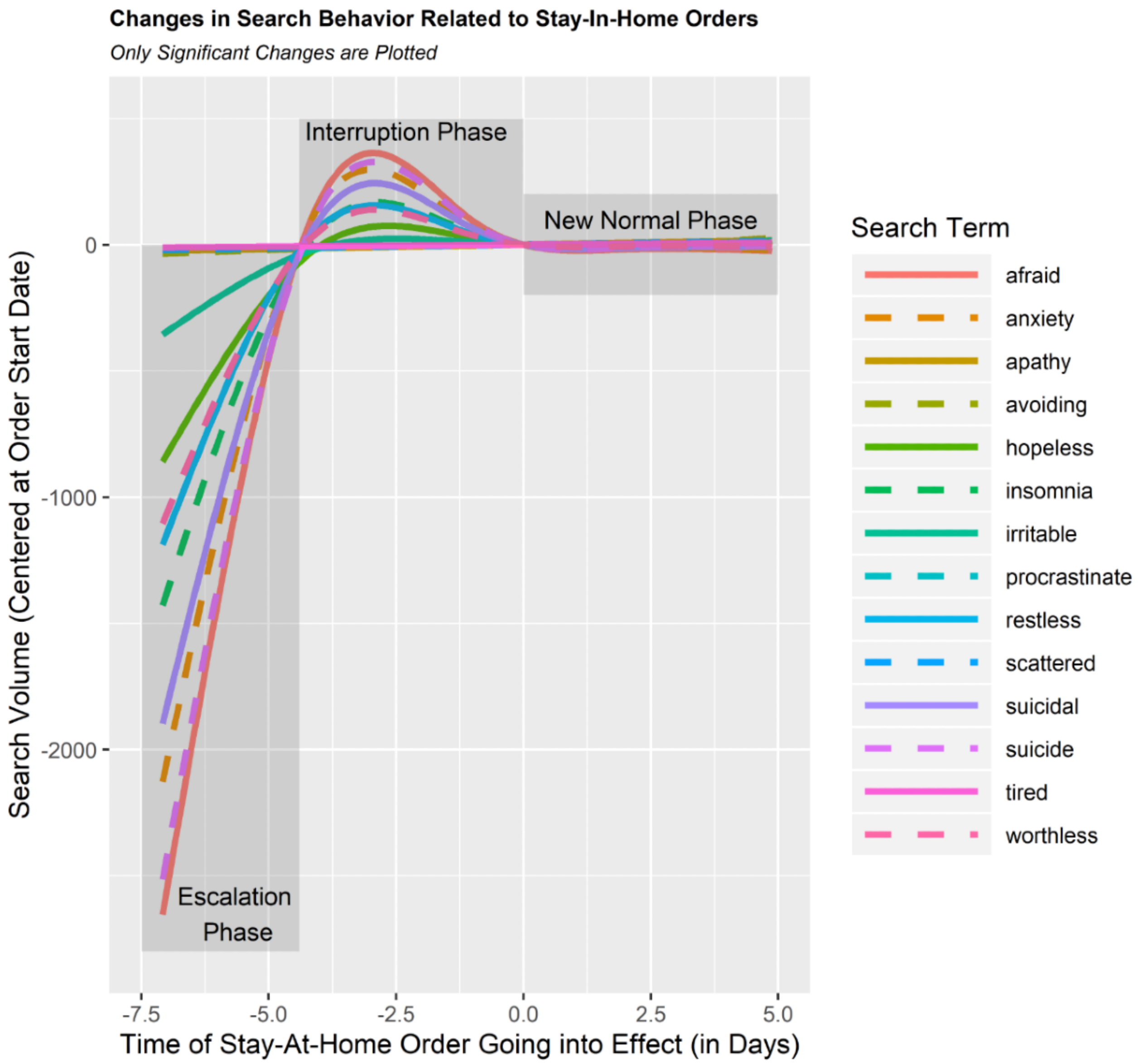
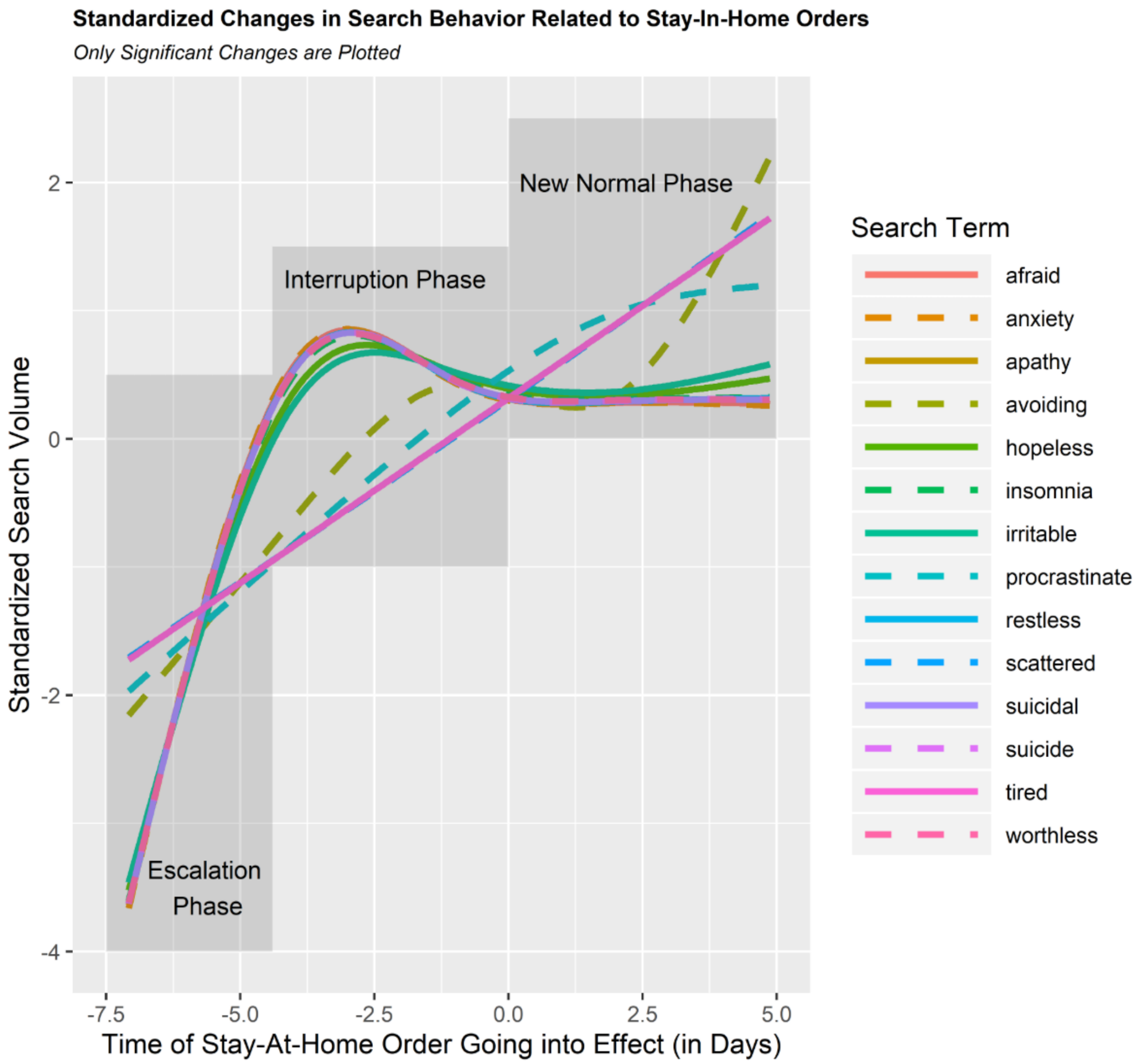


**Figure 4.** This plot depicts the standardized changes in search patterns relative to the orders going into effect. Values are normalized to reflect the relative change in these searches across time. Negative time of stay-at-home values reflect the time before the stay-at-home orders go into effect, and positive values reflect the time following the order going into effect. Values are standardized to show the relative pattern of the effect. The escalation phase designates approximately 4 days prior to the stay-at-home orders going into effect. The interruption phase spans between approximately 4 days and 0 days before the orders go into effect, and the new normal phase represents the times the 5 days after orders go into effect.



## Non-COVID-19 Physical Health Symptom Searches and Stay-at-Home Orders

In contrast to the mental health terms (where 14 of the 19 symptoms evidenced significant changes related to stay-at-home orders, 12 of which were associated with significant leveling off), only 7 of the 22 nonrelated physical health symptoms demonstrated changes over time related to the timing of stay-at-home orders (see Supplemental Table A1 in Multimedia Appendix 2). Of the 7, only 2 of these symptoms demonstrated a leveling-off effect (ie, flatulence and discharge). In addition, the effects of these symptoms were notably later and less extreme than those of the mental health symptoms (see Supplementary Figures A4 and A5 in Multimedia Appendix 1). Taken together, this suggests that the extreme leveling off associated with mental health symptoms was not replicated in the non-COVID-19 physical health symptoms.

## COVID-19 Physical Health Symptom Searches and Stay-at-Home Orders

Likewise, in contrast to mental health symptoms, only 6 of the 15 COVID-19 symptoms were significantly related to stay-at-home orders (see Supplemental Table A2 in Multimedia Appendix 2). Of these 6 symptoms, only 2 symptoms (fever and pain) were increasing before the initiation of the stay-at-home order, and they leveled off after the order was officially in place (see Supplementary Figures A6 and A7 in Multimedia Appendix 1). Note that the findings of the COVID-19 physical health symptoms continue to suggest that stay-at-home orders appear to more saliently impact mental health compared to COVID-19–related physical health.

## Discussion

This paper investigates the consequences of stay-at-home policies to prevent the spread of COVID-19 on changes in mental health symptom searches. The analysis is based on more than 10 million mental health Google searches within the United States. The results suggested that there were large shifts in mental health symptom searches linked to stay-at-home orders between the period of March 16-23, 2020. Particularly, the results indicated that topics related to anxiety (ie, fear, anxiety, avoiding, restlessness, procrastination), negative thoughts about oneself and the future (ie, hopelessness and worthless), sleep disturbances (ie, insomnia), and suicidal ideation (ie, suicide, suicidal) were each associated with dramatic increases prior to stay-at-home orders being announced with subsequent and considerable leveling off during these periods, approximately the same time as the stay-at-home orders were announced and enacted.

Notably, with few exceptions, these patterns were relatively unique to mental health search behaviors and not characteristic of other physical health conditions more broadly, thereby providing evidence to suggest that the largest changes were associated with mental health symptoms rather than COVID-19 symptoms across this short time frame. The consistency of these findings and their applicability to mental health domains highlights that they are likely not an artifact of the study methodology but rather reflect differences in search behaviors resulting from stay-at-home policy announcements and implementations.

Suicidality was one of the symptoms most greatly impacted by these stay-at-home orders. Importantly, prior studies have found robust associations between local Google suicide search queries and completed suicide rates [7,12], with extremely high interrater reliability (ICC=0.98) between searches for suicides and observed suicide rates [15]. Moreover, the early observed increase in “suicide” searches corroborates media reports that suicide calls have been increasing during the COVID-19 outbreak in the United States [29]. Thus, the current findings may point toward emerging evidence that stay-at-home orders may have immediately, at least temporarily, mitigated suicide risk. Although this research may point toward potential relationships between stay-at-home orders and actual suicide rates, research regarding observed suicide rates should be conducted to determine whether these patterns hold when examining actual suicide rates before any conclusions can be reached.

The current observation of rapid rises in anxiety symptom searches before the announcement of stay-at-home orders mirrors the trends of high prevalence rates of generalized anxiety disorder during the COVID-19 outbreak in China [30]. Nevertheless, the flattening of anxiety symptom searches suggest that the announcement and enactment of stay-at-home orders may have had an immediate effect on altering this rising trajectory, preventing further fears and unrest given known governmental action. Notably, the trends observed affirm prior research in China, which suggests that more clarity and action regarding precautionary COVID-19 measures leads to greater calming and lower levels of anxiety [16]. This highlights the importance of reducing uncertainty to foster mental health following disasters [24]. In turn, the societal impacts of governmental interventions in ameliorating the increase of anxiety during the COVID-19 pandemic is corroborated.

Notably, although these stay-at-home orders may have helped to flatten the staggering curvilinear increase in mental health symptom searches prior to the enactment of stay-at-home orders, the trend was not one in which these symptoms significantly decreased. Rather, the search rates remained relatively stable across the first days of a stay-at-home order going into effect. Certainly, more research will be needed to examine the long-term effects of these stay-at-home orders, especially given that longer quarantine orders have been associated with increased posttraumatic stress symptoms in prior work [31].

This study has many strengths. First, this study is the first known study to investigate the immediate impacts of stay-at-home measures during a pandemic on mental health. Second, having analyzed over 10 million search queries related to mental health across 1 week, the scope of the study methodology in examining mental health is unprecedented in size. Third, we were able to contrast the pre-post changes from these stay-at-home orders in contrast to other states in the same country to show deviations from the general pattern. Fourth, we isolated that these mental health terms were unique to mental health trajectories within the same time span by comparing the searches to changes in non-COVID-19–related and COVID-19–related physical symptoms.

Despite the study’s many strengths, the study also raises unanswered questions. Perhaps the greatest question is whether or not the flattening of these surges in mental health symptom searches is short-lived or if long-term stay-at-home orders will result in an abiding dampening of these symptoms. Thus, more research is needed to extend these findings to study the impacts of both COVID-19 and governmental responses to COVID-19 during this unprecedented time.

## Authors' Contributions

All authors made significant contributions to the manuscript. The following were the respective roles for each author: NJ contributed to the study design, hypothesis generation, data collection, data analysis, data interpretation, and manuscript write-up and review; DL contributed to the literature searches, data collection, figure creation, and manuscript write-up and review; GP contributed to the literature searches, data collection, and manuscript write-up and review; MH contributed to the literature searches and manuscript write-up and review; MS contributed to the literature searches and manuscript write-up and review; JO contributed to the study design, data analyses, data interpretation, and manuscript review; and PB contributed to the study design, literature searches, manuscript write-up, data interpretation, and manuscript review.

## Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplementary figures.
[DOCX File , 1380 KB - mental_v7i6e19347_app1.docx ]

Multimedia Appendix 2
Supplementary tables.
[DOCX File , 18 KB - mental_v7i6e19347_app2.docx ]

## References

1. Lai C, Shih T, Ko W, Tang H, Hsueh P. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and coronavirus disease-2019 (COVID-19): The epidemic and the challenges. Int J Antimicrob Agents 2020 Mar;55(3):105924 [FREE Full text] [doi: 10.1016/j.ijantimicag.2020.105924] [Medline: 32081636]
2. Zhou F, Yu T, Du R, Fan G, Liu Y, Liu Z, et al. Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. Lancet 2020 Mar;395(10229):1054-1062. [doi: 10.1016/S0140-6736(20)30566-3]
3. Hatchett RJ, Mecher CE, Lipsitch M. Public health interventions and epidemic intensity during the 1918 influenza pandemic. Proc Natl Acad Sci U S A 2007 May 01;104(18):7582-7587 [FREE Full text] [doi: 10.1073/pnas.0610941104] [Medline: 17416679]
4. Fauci AS, Lane HC, Redfield RR. Covid-19 — navigating the uncharted. N Engl J Med 2020 Mar 26;382(13):1268-1269. [doi: 10.1056/nejme2002387]
5. Lewnard JA, Lo NC. Scientific and ethical basis for social-distancing interventions against COVID-19. Lancet Infect Dis 2020 Mar. [doi: 10.1016/s1473-3099(20)30190-0]
6. Wang Y, Xu B, Zhao G, Cao R, He X, Fu S. Is quarantine related to immediate negative psychological consequences during the 2009 H1N1 epidemic? Gen Hosp Psychiatry 2011;33(1):75-77. [doi: 10.1016/j.genhosppsych.2010.11.001] [Medline: 21353131]
7. Yang A, Tsai SJ, Huang NE, Peng CK. Association of Internet search trends with suicide death in Taipei City, Taiwan, 2004-2009. J Affect Disord 2011 Jul;132(1-2):179-184. [doi: 10.1016/j.jad.2011.01.019] [Medline: 21371755]
8. Sueki H. Does the volume of Internet searches using suicide-related search terms influence the suicide death rate: data from 2004 to 2009 in Japan. Psychiatry Clin Neurosci 2011 Jun;65(4):392-394. [doi: 10.1111/j.1440-1819.2011.02216.x] [Medline: 21569178]
9. Kristoufek L, Moat HS, Preis T. Estimating suicide occurrence statistics using Google Trends. EPJ Data Sci 2016;5(1):32 [FREE Full text] [doi: 10.1140/epjds/s13688-016-0094-0] [Medline: 32355600]
10. Parker J, Cuthbertson C, Loveridge S, Skidmore M, Dyar W. Forecasting state-level premature deaths from alcohol, drugs, and suicides using Google Trends data. J Affect Disord 2017 Apr 15;213:9-15. [doi: 10.1016/j.jad.2016.10.038] [Medline: 28171770]
11. McCarthy MJ. Internet monitoring of suicide risk in the population. J Affect Disord 2010 May;122(3):277-279 [FREE Full text] [doi: 10.1016/j.jad.2009.08.015] [Medline: 19748681]
12. Barros JM, Melia R, Francis K, Bogue J, O'Sullivan M, Young K, et al. The validity of Google Trends search volumes for behavioral forecasting of national suicide rates in Ireland. Int J Environ Res Public Health 2019 Sep 02;16(17) [FREE Full text] [doi: 10.3390/ijerph16173201] [Medline: 31480718]
13. Waszak PM, Górski P, Springer J, Kasprzycka-Waszak W, Duży M, Zagożdżon P. Internet searches for "suicide", its association with epidemiological data and insights for prevention programs. Psychiatr Danub 2018 Dec;30(4):404-409 [FREE Full text] [doi: 10.24869/psyd.2018.404] [Medline: 30439800]
14. Gunn JF, Lester D. Using Google searches on the internet to monitor suicidal behavior. J Affect Disord 2013 Jun;148(2-3):411-412. [doi: 10.1016/j.jad.2012.11.004] [Medline: 23182592]
15. Lee J. Search trends preceding increases in suicide: a cross-correlation study of monthly Google search volume and suicide rate using transfer function models. J Affect Disord 2020 Feb 01;262:155-164. [doi: 10.1016/j.jad.2019.11.014] [Medline: 31733460]
16. Wang C, Pan R, Wan X, Tan Y, Xu L, Ho CS, et al. Immediate psychological responses and associated factors during the initial stage of the 2019 coronavirus disease (COVID-19) epidemic among the general population in China. Int J Environ Res Public Health 2020 Mar 06;17(5) [FREE Full text] [doi: 10.3390/ijerph17051729] [Medline: 32155789]
17. Brooks SK, Webster RK, Smith LE, Woodland L, Wessely S, Greenberg N, et al. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. Lancet 2020 Mar;395(10227):912-920. [doi: 10.1016/s0140-6736(20)30460-8]
18. Massicotte P, Eddelbuettel D. gtrendsR: perform and display Google trends queries. R package version 2020.

19. COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU). URL: https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6
20. Soreni N, Cameron DH, Streiner DL, Rowa K, McCabe RE. Seasonality patterns of internet searches on mental health: exploratory infodemiology study. JMIR Ment Health 2019 Apr 24;6(4):e12974 [FREE Full text] [doi: 10.2196/12974] [Medline: 31017582]
21. American Psychiatric Association. Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Washington, DC: American Psychiatric Pub; 2013.
22. Fernandez KC, Fisher AJ, Chi C. Development and initial implementation of the Dynamic Assessment Treatment Algorithm (DATA). PLoS One 2017;12(6):e0178806 [FREE Full text] [doi: 10.1371/journal.pone.0178806] [Medline: 28654667]
23. Prasad V, Jena AB. Prespecified falsification end points: can they validate true observational associations? JAMA 2013 Jan 16;309(3):241-242. [doi: 10.1001/jama.2012.96867] [Medline: 23321761]
24. Polansky L, Robbins MM. Generalized additive mixed models for disentangling long-term trends, local anomalies, and seasonality in fruit tree phenology. Ecol Evol 2013 Sep;3(9):3141-3151. [doi: 10.1002/ece3.707] [Medline: 24102000]
25. Wood SN. Generalized Additive Models: An Introduction With R. Cleveland, OH: CRC Press; 2006:A.
26. Jacobson NC, Chow S, Newman MG. The Differential Time-Varying Effect Model (DTVEM): a tool for diagnosing and modeling time lags in intensive longitudinal data. Behav Res Methods 2019 Feb;51(1):295-315 [FREE Full text] [doi: 10.3758/s13428-018-1101-0] [Medline: 30120682]
27. Wood SN. Thin plate regression splines. J Royal Statistical Soc B 2003 Feb;65(1):95-114. [doi: 10.1111/1467-9868.00374]
28. Wood S. mgcv: mixed GAM computation vehicle with automatic smoothness estimation. R Package 2019.
29. KGW. 2020 Mar 24. Portland police chief says suicide calls are up during coronavirus outbreak URL: https://www.kgw.com/article/news/health/coronavirus/watch-portland-mayor-ted-wheeler-gives-updates-on-covid-19-response/283-20f9b2e2-14d2-45c0-a388-cabcb62b35c2
30. Huang Y, Zhao N. Generalized anxiety disorder, depressive symptoms and sleep quality during COVID-19 epidemic in China: a web-based cross-sectional survey. medRxiv 2020 Mar 09. [doi: 10.1101/2020.02.19.20025395]
31. Hawryluck L, Gold WL, Robinson S, Pogorski S, Galea S, Styra R. SARS control and psychological effects of quarantine, Toronto, Canada. Emerg Infect Dis 2004 Jul;10(7):1206-1212 [FREE Full text] [doi: 10.3201/eid1007.030703] [Medline: 15324539]

## Abbreviations

**COVID-19:** coronavirus disease
**GAMM:** generalized additive mixed model
**ICC:** intraclass correlation coefficient
**OCD:** obsessive-compulsive disorder

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Original Paper

# Using Internet-Based Psychological Measurement to Capture the Deteriorating Community Mental Health Profile During COVID-19: Observational Study

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## Abstract

**Background:** The coronavirus disease (COVID-19) is expected to have widespread and pervasive implications for mental health in terms of deteriorating outcomes and increased health service use, leading to calls for empirical research on mental health during the pandemic. Internet-based psychological measurement can play an important role in collecting imperative data, assisting to guide evidence-based decision making in practice and policy, and subsequently facilitating immediate reporting of measurement results to participants.

**Objective:** The aim of this study is to use an internet-based mental health measurement platform to compare the mental health profile of community members during COVID-19 with community members assessed before the pandemic.

**Methods:** This study uses an internet-based self-assessment tool to collect data on psychological distress, mental well-being, and resilience in community cohorts during (n=673) and prior to the pandemic (two cohorts, n=1264 and n=340).

**Results:** Our findings demonstrate significantly worse outcomes on all mental health measures for participants measured during COVID-19 compared to those measured before (*P*<.001 for all outcomes, effect sizes ranging between Cohen d=0.32 to Cohen d=0.81. Participants who demonstrated problematic scores for at least one of the mental health outcomes increased from 58% (n=197/340) before COVID-19 to 79% (n=532/673) during COVID-19, leading to only 21% (n=141) of measured participants displaying good mental health during the pandemic.

**Conclusions:** The results clearly demonstrate deterioration in mental health outcomes during COVID-19. Although further research is needed, our findings support the serious mental health implications of the pandemic and highlight the utility of internet-based data collection tools in providing evidence to innovate and strengthen practice and policy during and after the pandemic.

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**KEYWORDS**

psychological measurement; positive mental health; resilience; mental health; psychological distress; internet; COVID-19; pandemic

# Introduction

## Background

The advent of the coronavirus disease (COVID-19) and the widespread (social) control mechanisms implemented around the world are expected to lead to significant deterioration in mental health in the wider community; however, the magnitude of the damage is unknown [1,2]. The impact of the pandemic on health systems, the worsening economy and associated high rates of unemployment, the widespread social restrictions and quarantining, and the constant presentation of confronting news messages from the media are unprecedented challenges for communities and the mental health of its members [3-6].

It is crucial to thoroughly assess the potential community mental health consequences of the pandemic and gain insight into local data on mental health outcomes, as a shift in the mental health profile of the community will have short- and long-term consequences for health services, policy makers, and society in general. In addition to their ability to improve the psychological assessment process in general [7-9], internet-based measurement of mental health outcomes can play an important role in gathering data to inform policy and practice during and after the pandemic [10]. Such measurements inherently possess the ability to collect data on a large scale and facilitate immediate reporting on user mental health status, which ultimately can enhance participant mental health literacy and stimulate help-seeking behavior [11].

This is particularly relevant in light of the reduced ability and opportunity to conduct traditional assessments and screening for mental illness during COVID-19 as a result of physical distancing protocols. There is an important role to play for internet-based measurement of the general distress and well-being profile of the community, which is more suitable for online testing compared to assessment of specific disorders or severe mental illness. Higher rates of community distress and significant deterioration of positive and adaptive states of mental health—mental wellbeing and resilience—can signal the immediate and long-term presence of mental illness in the wider population [12-14]. As such, they are key indicators of the deterioration of mental health in the general community.

## The Australian Context

As of the June 2, 2020, Australia had a total of 7204 confirmed cases of COVID-19, resulting in 103 deaths (1.4% death rate) [15]. The first reported case of COVID-19 in Australia was on January 25, 2020, in Victoria [16]. The Australian Government Department of Health [17] reported that cases peaked in March, and since April, the number of identified cases have remained relatively low. Of the states and territories within Australia, on June 2, 2020, New South Wales had the highest number of COVID-19 cases (3104 cases), followed by Victoria (1663 cases), Queensland (1059 cases), Western Australia (591 cases), South Australia (440 cases), Tasmania (228 cases), Australian Capital Territory (107 cases), and Northern Territory (29 cases) [18]. To put these numbers in perspective, rates in Australia are approximately 282 per 1 million compared with 5184 in the United States, 4009 in the United Kingdom, and 3848 in Italy [19].

In an attempt to flatten the curve of COVID-19 in Australia, the Australian Government began to slowly introduce lockdown measures. On February 1, 2020, travelers from mainland China were required to self-isolate for a period of 14 days from the date they left China, but widespread societal measures were not considered. Early March 2020 saw the rise of panic buying in supermarkets, and, through the rest of the month, the federal and state governments established progressively tighter lockdown restrictions, including limiting social gatherings and nonessential travel, and lockdowns of gyms, bars, restaurants, and schools [20]. Other nonessential workplaces instructed their staff to work from home where possible. With the exception of minor incidents, the rules on restrictions were generally followed by the Australian population, despite its flow-on effects resulting in many thousands of people losing their livelihoods, as well as resulting in large-scale social change and restrictions of freedom.

## This Study

The impact of the COVID-19 pandemic in Australia has had a serious impact on a community and societal level. As a result, it could be expected to negatively impact mental health outcomes in the wider community, not simply limited to those directly affected or exposed to the illness. Therefore, it is important to quantify the local impact of the pandemic on community mental health outcomes, data that can feasibly be gathered using internet-based tools and methods. This study investigates the mental health outcomes of Australian community members accessing internet-based mental health assessment and psychological skills training during COVID-19 in comparison to cohorts of people engaged in these services prior to the pandemic.

# Methods

## Participants and Recruitment

Participants were adults who engaged with services offered by the South Australian Health and Medical Research Institute (SAHMRI) Wellbeing and Resilience Centre, based in Adelaide, Australia. The center provides internet-based measurement of mental health and well-being, and delivers general psychological skills training to the general community, with the aim of improving mental health and well-being.

Participants recruited during COVID-19 (hereafter, COVID-19 group) registered to participate in the study from March 29, 2020, onwards, well into the period of social restrictions in Australia, which occurred mid-March. Recruitment was conducted via two weblinks. The first was from the generic website of the Wellbeing and Resilience Centre, where people could find mental health resources and register for a free evidence-based mental health and well-being measurement. The second is a website that provides information about free online psychological skills training called the Be Well Plan, where participants could preregister and complete the same mental health and well-being measurement offered on the first website, prior to commencing the training.

Participants from the comparator cohort were adults who participated in mental health and well-being measurement and training between February 2019 and February 14, 2020, a month before social restrictions were implemented and when incidence of COVID-19 in Australia remained low. The first comparator cohort (general [GEN] group) consisted of participants who either took part in a group-based psychological skills training that was offered prior to COVID-19 or registered via the generic SAHMRI website for a free well-being measurement. Participants for the training included individuals from the public or people recruited for specific projects, for example, training provision to workforces. Participants from those projects were not community members reaching out on their own accord (ie, their employer may have directed them to participate), which meant their motivation could have been different to the COVID-19 cohort. This led to the creation of a second comparator cohort (help-seeking [HELP] group), consisting of individuals from the general population who engaged in the training or measurement of their own volition.

After registration, all participants completed the measurement online via internet-enabled devices (approximately 10-15 minutes to complete). The measurement captured basic demographic information (ie, gender, age, employment, and study status) to keep questionnaire burden low. After completing the measurement, participants were automatically provided with their individual scores and an individualized online report that explained the results and provided information about subsequent options to improve their mental health, as well as information on mental health services in case of immediate need.

### Outcome Measures

The measurement included items assessing psychological distress associated with symptoms of depression and anxiety, as well as positive (mental well-being) and adaptive (resilience) states. Psychological distress was measured using the Depression Anxiety and Stress Scale-21 items (DASS-21) [21]. The DASS-21 offers reliable cut-off points for symptom severity (ie, “mild,” “moderate,” “severe,” and “extremely severe” symptoms). Analyses were conducted using total scores for each of the three domains; internal consistencies for depression (α=.92), anxiety (α=.84), and stress (α=.86) were good. Well-being was measured using the Mental Health Continuum Short-Form (MHC-SF) [22]. The MHC-SF is a valid and reliable measure of mental well-being, providing both a continuous measure of three key domains of well-being (hedonic, eudaimonic, and social well-being), as well as a “diagnosis” of overall well-being into “flourishing” or high well-being, moderate well-being, and “languishing” or low well-being. Internal consistency was assessed on the summed total score of all 14 items (α=.94). An additional well-being measure was used to specifically capture satisfaction with life. The Satisfaction With Life Scale [23] is a universally accepted measure, demonstrating high internal consistency (α=.91). Adaptive states were measured using the Brief Resilience Scale (BRS) [24]. The BRS conceptualizes resilience as an outcome and is a well-accepted tool to gain insight into resilience, with cut-offs for low, normal, and high resilience. Internal consistency was high, α=.88.

### Data Analysis

Independent samples *t* tests and chi-square tests were conducted to investigate demographic differences between groups. Differences between groups were assessed using multivariate analysis of variance to test for an overall difference between conditions and subsequent analyses of variance to test for differences in each dependent variable. Covariates were entered to control for any baseline differences between the groups in the analyses. Given that all dependent variables were moderately correlated, a Bonferroni correction for multiple comparisons was employed, using an alpha level of =.008. Listwise deletion was employed to handle missing data. The previously mentioned measurement cut-offs were used to determine whether participants were “healthy” compared to participants who demonstrated distress or at-risk scores; healthy participants referred to high levels of well-being, normal levels of resilience, and no symptoms of distress in any of the three domains.

## Results

The COVID-19 group consisted of 673 participants, while the control cohorts consisted of 1264 participants and 340 participants from the GEN group and HELP group, respectively. Demographic characteristics of the cohorts are reported in Table 1. There were less males in the COVID-19 sample compared to the two control cohorts ($\chi^2_2$=194.1, $P<.001$), and the average age in the COVID-19 cohort was marginally higher ($F_{2,2274}$=3.56, $P$=.03, $\eta^2_{partial}$=0.003). A significant difference also existed in the proportion of participants employed ($\chi^2_2$=243.1, $P<.001$), as the COVID-19 cohort consisted of more unemployed participants. Finally, there were significantly less people studying in the GEN group compared to the other two cohorts ($\chi^2_2$=243.1, $P<.001$) in each sample. As a result, age, gender, study, and employment status were controlled for in the subsequent analyses.

**Table 1.** Demographics.

| Demographic | COVID-19[a] (n=673)[b] | GEN[c] (n=1264)[d] | HELP[e] (n=340)[f] |
|---|---|---|---|
| Age (years), mean (SD) | 44.8 (14.7) | 42.7 (11.4) | 42.6 (11.8) |
| Gender (female), n (%) | 437 (65) | 583 (46) | 198 (58) |
| Unemployed, n (%) | 168 (25) | 30 (2) | 36 (11) |
| Studying, n (%) | 107 (16) | 46 (4) | 53 (16) |

[a] COVID-19: coronavirus disease.

[b] The COVID-19 cohort consists of participants recruited in March and April 2020.

[c] GEN: general.

[d] The GEN cohort consists of participants engaging in mental health training and measurement during February 2019 to February 2020.

[e] HELP: help-seeking.

[f] The HELP cohort is a subset of the general cohort, which consists of users who reached out to the service on their own accord (as opposed to being invited as part of a specific project).

There was a significant multivariate difference between the three samples on all outcome measures (Pillai $V$=0.17, $F_{2,2268}$=35.66, $P$<.001, $\eta^2_{partial}$=0.06; refer to Table 2 for means and SDs for all outcome variables). Subsequent univariate analyses indicated a significant difference between the cohorts on depression ($F_{2,2268}$=93.8, $P$<.001, $\eta^2_{partial}$=0.051), stress ($F_{2,2268}$=47.8, $P$<.001, $\eta^2_{partial}$=0.066), anxiety ($F_{2,2268}$=108.8, $P$<.001, $\eta^2_{partial}$=0.031), well-being ($F_{2,2268}$=28.8, $P$<.001, $\eta^2_{partial}$=0.017), life satisfaction ($F_{2,2268}$=44.2, $P$<.001, $\eta^2_{partial}$=0.020), and resilience ($F_{2,2268}$=150.5, $P$<.001, $\eta^2_{partial}$=0.075). Tukey post-hoc comparisons indicated that the COVID-19 cohort showed significantly worse outcomes compared to both control cohorts on depression, stress, anxiety, well-being, life satisfaction, and resilience (Table 2). No differences between the two control cohorts were found for general well-being, life satisfaction, depression, and anxiety. The GEN group differed significantly from the HELP group in stress and resilience, with the HELP group showing worse outcomes.

**Table 2.** Means and SDs for the COVID-19 and control cohorts.

| Variables | COVID-19[a,b], mean (SD) | GEN[c,d], mean (SD) | HELP[e,f], mean (SD) | COVID-19 vs GEN | | COVID-19 vs HELP | | GEN vs HELP | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Cohen *d*[g] | *P* value | Cohen *d* | *P* value | Cohen *d* | *P* value |
| Depression | 12.69 (10.56) | 6.79 (8.52) | 8.05 (8.63) | 0.62 | <.001 | 0.48 | <.001 | 0.15 | .06 |
| Stress | 16.11 (9.48) | 10.14 (8.29) | 12.48 (8.66) | 0.67 | <.001 | 0.40 | <.001 | 0.28 | <.001 |
| Anxiety | 8.41 (8.01) | 5.22 (6.60) | 5.84 (6.67) | 0.44 | <.001 | 0.35 | <.001 | 0.09 | .30 |
| Well-being | 42.87 (14.30) | 47.35 (12.98) | 47.85 (12.59) | 0.33 | <.001 | 0.370 | <.001 | 0.04 | .81 |
| Life satisfaction | 20.86 (6.98) | 23.80 (6.55) | 22.93 (6.11) | 0.43 | <.001 | 0.32 | <.001 | 0.14 | .08 |
| Resilience | 3.13 (0.81) | 3.82 (0.90) | 3.40 (0.81) | 0.81 | <.001 | 0.33 | <.001 | 0.49 | <.001 |

[a] COVID-19: coronavirus disease.

[b] The COVID-19 group consists of participants recruited in March and April 2020.

[c] GEN: general.

[d] The GEN group consists of participants who engaged in mental health training and measurement during February 2019 to February 2020.

[e] HELP: help-seeking.

[f] The HELP group is a subset of the general cohort, which consists of users reaching out on their own accord.

[g] Effect sizes were calculated using Cohen *d*, where 0.2 is a small effect, 0.5 is a medium effect, and 0.8 is a large effect.

Finally, the study investigated the proportion of participants that displayed problematic scores on at least one of the outcomes (ie, the proportion of participants with mental health problems). The COVID-19 cohort displayed a significantly higher proportion (n=532/673, 79%) of participants reporting problematic mental health outcomes, compared to the GEN (n=657/1264, 52%; $\chi^2_2$=135.78, $P$<.001) and HELP cohort (n=197/340, 58%; $\chi^2_2$=49.88, $P$<.001).

## Discussion

Our findings suggest a significant deterioration of mental health profiles for general community members engaging with mental health services during COVID-19 compared to before the global pandemic. All indicators of psychological distress as well as indicators of mental well-being and resilience were significantly lower, providing evidence to indicate the pervasive short-term mental health impact of the pandemic and the heightened risk of mental illness onset in the future for the general community [1,25].

The psychological impact of the COVID-19 pandemic observed in this study aligns with emerging global research and research into previous pandemics and disasters—research that largely focuses on distress and mental illness. Rajkumar [26] conducted a review of the literature related to mental health and the COVID-19 pandemic, indicating that elevated levels of anxiety, depression, and stress were the most common psychological reactions to COVID-19. Although this study did not investigate the exact mechanisms underpinning the psychological distress, the review also identified editorials and commentaries describing the potential mental health impacts of the pandemic, drawing from previous disease outbreaks. Unpredictability, uncertainty, severity of the diseases, social isolation and loneliness, misinformation, and economic impacts were cited among the factors most likely associated with the increased psychological distress [27,28]. Similar results on psychological distress were found in the context of the Korean Middles East respiratory syndrome outbreak [29], in medical staff following the Ebola outbreak in African nations [30], and in the severe acute respiratory syndrome–related coronavirus outbreak in Taiwan [31].

The impact of pandemics or lockdowns on positive and adaptive mental health states such as mental well-being has been researched far less than the impact on psychological distress; however, several determinants of mental well-being are impeded during the lockdowns. The clearest impact of the lockdown is on personal agency and autonomy, key determinants of psychological well-being and self-determination theory [32,33]. Recent research has validated the importance of loss in agency, showing that it may have a significant impact on levels of life satisfaction [34]. Physical activity is another strong determinant of mental well-being and distress, and a protective factor against psychological distress, which has been impacted by COVID-19–related restrictions [35]. The closure of gyms, sporting clubs, public parks, and recreational areas may have contributed to the results observed in this study [36]. Other important drivers of well-being [37] that were affected, and therefore can play a role in explaining the results found here, include spirituality and interpersonal relationships—as a result from places of worship, restaurants, bars, and universities closing—the loss of purpose or meaning in life due to financial distress or loss of employment, significant changes to lifestyle such as homeschooling children, and social isolation and loneliness to name a few.

The significant levels of distress in the current cohorts of Australian community members are alarming. First, they flag a deterioration of mental health profiles among the general nonclinical population, suggesting an urgent need for prevention or early intervention to improve mental health and well-being, and equip people with resources to better cope in times of adversity [25]. Mental well-being is a known protective factor from psychological distress and mental illness [14,38]; therefore, the deterioration in mental well-being is a cause for concern for the mental health in the mid- and long-term of the pandemic. Second, it is likely that levels of distress among people with mental disorders are even higher, pointing to an urgent need for local research and subsequently intervention when this is confirmed.

The HELP cohort was, on average, less resilient and experienced higher levels of stress compared to the GEN control cohort. The HELP cohort was constructed to lower the impact of bias between the COVID-19 group and the control group, as both the HELP and the COVID-19 cohorts proactively engaged with the services on their own volition. The results found in the study however make intuitive sense. Specifically, it can be expected that individuals suffering from increased levels of stress in their lives will seek out mental health service offerings to alleviate their stress. We further expect to see individuals low in self-reported levels of resilience (the measure of resilience used here focuses on feeling resilient to cope with stressful times [24]) to seek out the program to increase their self-perceived resilience. Taking these findings into account further highlights the impact of COVID-19 on participants mental health, as the COVID-19 cohort significantly deviated on all outcomes from the HELP cohort.

The results need to be placed in the Australian context, where the impact of COVID-19 has been less severe compared to countries in Europe or the United States and social control has been less restrictive. Furthermore, although the participants in this sample were seeking out mental health services, they most likely largely represented a nonclinical community sample. Significant levels of psychological distress were observed in participants, which may indicate the presence of mental disorders in some of the participants; the current findings should, however, not simply be generalized to demonstrate the impact of COVID-19 on people with (severe) mental disorders [39].

A silver lining to these results can be found, as the pandemic has triggered significant interest in mental health, and signs of acceleration and innovation in the way we measure and support mental health can already be seen; for example, increased access to electronic health apps for mental health [40,41]. The measurement used in this study was freely accessible via internet-enabled devices and resulted in an immediate, individualized report for the participants. Improving access to internet-based services can act as an important complement to face-to-face measurement methods, as it may reduce barriers to seeking help [42]. Harnessing internet-based innovations in mental health service provision can stimulate wider mental health reform and help strengthen services for the entire population, regardless of the presence of (severe) mental disorders [43]. This is particularly important in relation to access to mental health services for vulnerable groups. The results here, for instance, suggest that unemployed people are reaching out for help with their mental health, which, in light of the mass unemployment recorded around the world, has important implications for mental health care services resourcing across the spectrum [44].

A number of areas, highlighted by our findings, will provide fruitful avenues for future research. First, although we have shown that COVID-19 had a detrimental impact on participant’s mental health in general, understanding specifically the effects that COVID-19 may exert on people already experiencing a mental illness is important [1]. This pandemic may have compounded the issues already faced by a proportion of the population, particularly those who are the most vulnerable; understanding this interaction is the first step to providing more effective help to at-risk and mentally ill people in the community while facing adversity. Second, our findings suggest that the COVID-19 pandemic, as a whole, was detrimental to individuals' mental health. However, our findings were unable to disentangle the specific mechanisms of decreased mental health during this pandemic. For instance, was social isolation the primary driver of decreased mental health, was it the loss of economic certainty, or was it caused more so by fear induced by media reporting? Future in-depth research of which determinants underpin the mental health impact of pandemics is required (eg, the role of social determinants of health [45]). Third, research and intervention aimed to improve psychological resilience may prove an economical way to improve community coping with large scale negative events. Future research on the mental skills that foster psychological resilience will enable the promotion of positive mental health in general and during widespread negative events [46], such as a pandemic, thus reducing the negative psychological impact of these events on the community.

In summary, more research is needed, particularly in monitoring the long-term consequences and determining the clinical impact of COVID-19 in different populations. This study is limited in its use of generic outcomes and its cross-sectional design. This means that more rigorously controlled studies are essential to capture the complexity of mental health amid a global pandemic. Our findings, however, demonstrate the utility of internet-based psychological measurement and contribute valuable data to equip stakeholders with evidence to further understand the considerable negative consequences of the COVID-19 pandemic—results that can be used to intervene and prevent amplification of its impact on community mental health.

## Conflicts of Interest

None declared.

## References

1. Holmes EA, O'Connor RC, Perry VH, Tracey I, Wessely S, Arseneault L, et al. Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science. Lancet Psychiatry 2020 Jun;7(6):547-560. [doi: 10.1016/s2215-0366(20)30168-1]
2. Gunnell D, Appleby L, Arensman E, Hawton K, John A, Kapur N, et al. Suicide risk and prevention during the COVID-19 pandemic. Lancet Psychiatry 2020 Jun;7(6):468-471. [doi: 10.1016/s2215-0366(20)30171-1]
3. Wahlbeck K, McDaid D. Actions to alleviate the mental health impact of the economic crisis. World Psychiatry 2012 Oct;11(3):139-145 [FREE Full text] [doi: 10.1002/j.2051-5545.2012.tb00114.x] [Medline: 23024664]
4. Pfefferbaum B, Newman E, Nelson SD, Nitiéma P, Pfefferbaum RL, Rahman A. Disaster media coverage and psychological outcomes: descriptive findings in the extant research. Curr Psychiatry Rep 2014 Sep;16(9):464 [FREE Full text] [doi: 10.1007/s11920-014-0464-x] [Medline: 25064691]
5. Brooks SK, Webster RK, Smith LE, Woodland L, Wessely S, Greenberg N, et al. The psychological impact of quarantine and how to reduce it: rapid review of the evidence. Lancet 2020 Mar;395(10227):912-920. [doi: 10.1016/s0140-6736(20)30460-8]
6. Galletly C. Psychiatry in the COVID-19 Era. Aust N Z J Psychiatry 2020 May;54(5):447-448. [doi: 10.1177/0004867420920359] [Medline: 32370594]
7. Bradford S, Rickwood D. Young people's views on electronic mental health assessment: prefer to type than talk? J Child Fam Stud 2015;24(5):1213-1221 [FREE Full text] [doi: 10.1007/s10826-014-9929-0] [Medline: 25960628]
8. Gibbons RD, Weiss DJ, Kupfer DJ, Frank E, Fagiolini A, Grochocinski VJ, et al. Using computerized adaptive testing to reduce the burden of mental health assessment. Psychiatr Serv 2008 Apr;59(4):361-368 [FREE Full text] [doi: 10.1176/ps.2008.59.4.361] [Medline: 18378832]
9. Barak A. Internet-based psychological testing and assessment. In: Online Counseling. Amsterdam, Netherlands: Elsevier; 2011:225-255.
10. Zhou X, Snoswell CL, Harding LE, Bambling M, Edirippulige S, Bai X, et al. The role of telehealth in reducing the mental health burden from COVID-19. Telemed J E Health 2020 Apr;26(4):377-379. [doi: 10.1089/tmj.2020.0068] [Medline: 32202977]
11. Jorm AF. Mental health literacy: empowering the community to take action for better mental health. Am Psychol 2012 Apr;67(3):231-243. [doi: 10.1037/a0025957] [Medline: 22040221]
12. Wood AM, Joseph S. The absence of positive psychological (eudemonic) well-being as a risk factor for depression: a ten year cohort study. J Affect Disord 2010 May;122(3):213-217. [doi: 10.1016/j.jad.2009.06.032] [Medline: 19706357]
13. Keyes CLM, Dhingra SS, Simoes EJ. Change in level of positive mental health as a predictor of future risk of mental illness. Am J Public Health 2010 Dec;100(12):2366-2371. [doi: 10.2105/ajph.2010.192245]
14. Keyes CL, Yao J, Hybels CF, Milstein G, Proeschold-Bell RJ. Are changes in positive mental health associated with increased likelihood of depression over a two year period? A test of the mental health promotion and protection hypotheses. J Affect Disord 2020 Jun 01;270:136-142. [doi: 10.1016/j.jad.2020.03.056] [Medline: 32339105]

15. Australian Government Department of Health. 2020. Coronavirus (COVID-19) current situation and case numbers URL: https://www.health.gov.au/news/health-alerts/novel-coronavirus-2019-ncov-health-alert/coronavirus-covid-19-current-situation-and-case-numbers
16. Ting I, Palmer A. ABC News. 2020 May 03. One hundred days of the coronavirus crisis URL: https://www.abc.net.au/news/2020-05-04/charting-100-days-of-the-coronavirus-crisis-in-australia/12197884?nw=0
17. Australian Government Department of Health. 2020. Daily number of reported COVID-19 cases in Australia URL: https://www.health.gov.au/resources/daily-number-of-reported-covid-19-cases-in-australia
18. O'Brien J. Covid19data.com. 2020. Coronavirus (COVID-19) in Australia URL: https://www.covid19data.com.au/states-and-territories
19. World Health Organization. 2020. WHO coronavirus disease (COVID-19) dashboard URL: https://covid19.who.int/
20. Woods J. Mondaq. 2020 May 07. Australia: timeline of key social & economic COVID-19 events affecting Australian business URL: https://www.mondaq.com/australia/operational-impacts-and-strategy/929622/timeline-of-key-social-economic-covid-19-events-affecting-australian-business
21. Henry J, Crawford J. The short-form version of the Depression Anxiety Stress Scales (DASS-21): construct validity and normative data in a large non-clinical sample. Br J Clin Psychol 2005 Jun;44(Pt 2):227-239. [doi: 10.1348/014466505X29657] [Medline: 16004657]
22. Keyes CLM, Wissing M, Potgieter JP, Temane M, Kruger A, van Rooy S. Evaluation of the mental health continuum-short form (MHC-SF) in setswana-speaking South Africans. Clin Psychol Psychother 2008;15(3):181-192. [doi: 10.1002/cpp.572] [Medline: 19115439]
23. Diener E, Emmons RA, Larsen RJ, Griffin S. The satisfaction with life scale. J Pers Assess 1985 Feb;49(1):71-75. [doi: 10.1207/s15327752jpa4901_13] [Medline: 16367493]
24. Smith BW, Dalen J, Wiggins K, Tooley E, Christopher P, Bernard J. The brief resilience scale: assessing the ability to bounce back. Int J Behav Med 2008;15(3):194-200. [doi: 10.1080/10705500802222972] [Medline: 18696313]
25. Fiorillo A, Gorwood P. The consequences of the COVID-19 pandemic on mental health and implications for clinical practice. Eur Psychiatry 2020 Apr 01;63(1):e32 [FREE Full text] [doi: 10.1192/j.eurpsy.2020.35] [Medline: 32234102]
26. Rajkumar RP. COVID-19 and mental health: a review of the existing literature. Asian J Psychiatr 2020 Apr 10;52:102066. [doi: 10.1016/j.ajp.2020.102066] [Medline: 32302935]
27. Zandifar A, Badrfam R. Iranian mental health during the COVID-19 epidemic. Asian J Psychiatr 2020 Mar 04;51:101990 [FREE Full text] [doi: 10.1016/j.ajp.2020.101990] [Medline: 32163908]
28. Shigemura J, Ursano R, Morganstein J, Kurosawa M, Benedek D. Public responses to the novel 2019 coronavirus (2019-nCoV) in Japan: mental health consequences and target populations. Psychiatry Clin Neurosci 2020 Apr;74(4):281-282 [FREE Full text] [doi: 10.1111/pcn.12988] [Medline: 32034840]
29. Kim YG, Moon H, Kim S, Lee Y, Jeong D, Kim K, et al. Inevitable isolation and the change of stress markers in hemodialysis patients during the 2015 MERS-CoV outbreak in Korea. Sci Rep 2019 Apr 05;9(1):5676. [doi: 10.1038/s41598-019-41964-x] [Medline: 30952879]
30. Park J, Lee E, Park N, Choi YH. Mental health of nurses working at a government-designated hospital during a MERS-CoV outbreak: a cross-sectional study. Arch Psychiatr Nurs 2018 Feb;32(1):2-6 [FREE Full text] [doi: 10.1016/j.apnu.2017.09.006] [Medline: 29413067]
31. Lee SM, Kang WS, Cho A, Kim T, Park JK. Psychological impact of the 2015 MERS outbreak on hospital workers and quarantined hemodialysis patients. Compr Psychiatry 2018 Nov;87:123-127 [FREE Full text] [doi: 10.1016/j.comppsych.2018.10.003] [Medline: 30343247]
32. Ryff CD, Keyes CLM. The structure of psychological well-being revisited. J Pers Soc Psychol 1995;69(4):719-727. [doi: 10.1037/0022-3514.69.4.719]
33. Ryan RM, Deci EL. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. Am Psychol 2000;55(1):68-78. [doi: 10.1037/0003-066x.55.1.68]
34. Hojman DA, Miranda Á. Agency, human dignity, and subjective well-being. World Dev 2018 Jan;101:1-15. [doi: 10.1016/j.worlddev.2017.07.029]
35. Balchin R, Linde J, Blackhurst D, Rauch HL, Schönbächler G. Sweating away depression? The impact of intensive exercise on depression. J Affect Disord 2016 Aug;200:218-221. [doi: 10.1016/j.jad.2016.04.030] [Medline: 27137088]
36. Fitzsimmons C. Sydney Morning Herald. 2020 May 31. Fitness lobby pressures politicians over 'totally illogical' gym closures URL: https://www.smh.com.au/national/nsw/fitness-lobby-pressures-politicians-over-totally-illogical-gym-closures-20200529-p54xw4.html
37. Diener E, Oishi S. Handbook of Well-Being. Salt Lake City, UT: Noba Scholar; 2018.
38. Trzebiński J, Cabański M, Czarnecka JZ. Reaction to the COVID-19 pandemic: the influence of meaning in life, life satisfaction, and assumptions on world orderliness and positivity. J Loss Trauma 2020 May 21:1-14. [doi: 10.1080/15325024.2020.1765098]
39. Druss BG. Addressing the COVID-19 pandemic in populations with serious mental illness. JAMA Psychiatry 2020 Apr 03. [doi: 10.1001/jamapsychiatry.2020.0894] [Medline: 32242888]

40. Wind TR, Rijkeboer M, Andersson G, Riper H. The COVID-19 pandemic: the 'black swan' for mental health care and a turning point for e-health. Internet Interv 2020 Apr;20:100317 [FREE Full text] [doi: 10.1016/j.invent.2020.100317] [Medline: 32289019]
41. Torous J, Jän Myrick K, Rauseo-Ricupero N, Firth J. Digital mental health and COVID-19: using technology today to accelerate the curve on access and quality tomorrow. JMIR Ment Health 2020 Mar 26;7(3):e18848 [FREE Full text] [doi: 10.2196/18848] [Medline: 32213476]
42. Pretorius C, Chambers D, Coyle D. Young people's online help-seeking and mental health difficulties: systematic narrative review. J Med Internet Res 2019 Nov 19;21(11):e13873 [FREE Full text] [doi: 10.2196/13873] [Medline: 31742562]
43. Iasiello M, van Agteren J, Muir-Cochrane E. Mental health and/or mental illness: a scoping review of the evidence and implications of the dual-continua model of mental health. Evidence Base 2020 Mar 18. [doi: 10.21307/eb-2020-001]
44. Kawohl W, Nordt C. COVID-19, unemployment, and suicide. Lancet Psychiatry 2020 May;7(5):389-390. [doi: 10.1016/s2215-0366(20)30141-3]
45. Lund C, Brooke-Sumner C, Baingana F, Baron EC, Breuer E, Chandra P, et al. Social determinants of mental disorders and the Sustainable Development Goals: a systematic review of reviews. Lancet Psychiatry 2018 Apr;5(4):357-369. [doi: 10.1016/s2215-0366(18)30060-9]
46. Tiernan A, Drennan L, Nalau J, Onyango E, Morrissey L, Mackey B. A review of themes in disaster resilience literature and international practice since 2012. Policy Design Pract 2018 Oct 25;2(1):53-74. [doi: 10.1080/25741292.2018.1507240]

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## Abbreviations

**BRS:** Brief Resilience Scale
**COVID-19:** coronavirus disease
**DASS-21:** Depression Anxiety and Stress Scale-21 items
**GEN:** general
**HELP:** help-seeking
**MHC-SF:** Mental Health Continuum Short-Form
**SAHMRI:** South Australian Health and Medical Research Institute

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