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Original Paper

E-Learning to Improve Suicide Prevention Practice Skills Among Undergraduate Psychology Students: Randomized Controlled Trial

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Abstract

Background: Despite increasing evidence of the effectiveness of digital learning solutions in higher vocational education, including the training of allied health professionals, the impact of Web-based training on the development of practical skills in psychiatry and psychology, in general, and in suicide prevention, specifically, remains largely understudied.

Objective: This study aimed to determine the effectiveness of an electronic learning (e-learning) module on the adherence to suicide prevention guidelines, knowledge of practical skills, and provider's confidence to have a conversation about suicidal behavior with undergraduate psychology students.

Methods: The e-learning module, comprising video recordings of therapist-patient interactions, was designed with the aim of transferring knowledge about suicide prevention guideline recommendations. The program's effects on guideline adherence, self-evaluated knowledge, and provider's confidence were assessed using online questionnaires before the program (baseline and at 1 month [T1] and 3 months after baseline). The eligible third- and fourth-year undergraduate psychology students were randomly allocated to the e-learning (n=211) or to a waitlist control condition (n=187), with access to the intervention after T1.

Results: Overall, the students evaluated e-learning in a fairly positive manner. The intention-to-treat analysis showed that the students in the intervention condition (n=211) reported higher levels of self-evaluated knowledge, provider's confidence, and guideline adherence than those in the waitlist control condition (n=187) after receiving the e-learning module (all P values<.001). When comparing the scores at the 1- and 3-month follow-up, after both groups had received access to the e-learning module, the completers-only analysis showed that the levels of knowledge, guideline adherence, and confidence remained constant (all P values>.05) within the intervention group, whereas a significant improvement was observed in the waitlist control group (all P values<.05).

Conclusions: An e-learning intervention on suicide prevention could be an effective first step toward improved knowledge of clinical skills. The learning outcomes of a stand-alone module were found to be similar to those of a training that combined e-learning with a face-to-face training, with the advantages of flexibility and low costs.

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KEYWORDS

e-learning; suicide prevention; digital learning; skills training; randomized controlled trial; undergraduate students

Introduction

Background

Suicide is currently one of the most common causes of death in the Netherlands, with rates of approximately 11 cases per 100,000 inhabitants since 2013 [1,2]. With suicide being an obvious public health concern, health care professionals need to direct efforts toward reducing suicide rates. However, health professionals are not well equipped because they receive little training that specifically prepares them to address suicidal behavior. For example, a common misperception prevails that asking about suicidality could evoke suicidal thoughts [3] even though studies have shown that asking patients about suicidality can evoke feelings of relief and openness, which in turn can ensure timely treatment and prevent exacerbation of symptoms [4,5]. Therefore, the clinician's proficiency in discussing suicidal thoughts is crucial for estimating the risk for suicide attempts, and so is the clinician's confidence in exercising these specific skills.

The advances in technology, rising costs in health care, and need for continuous education of allied health professionals have made electronic learning (e-learning) a popular educational method, specifically in skills education [6-8]. In both undergraduate and graduate medical programs, the use of e-learning modules is widespread [9-11]. It is used successfully in several branches of medicine and specialties, such as dermatology and surgery [12], as these modules allow for the teaching of concrete and measurable skills such as skin examination. In comparison, e-learning has been applied less frequently in the field of psychiatry [9,11] because direct patient contact is deemed most instructive to master interpersonal professional skills [13]. However, the results of a systematic review on the effectiveness of e-learning programs on clinician behavior and patient outcomes showed that e-learning programs are as effective as traditional learning approaches [14] and show superior results in improving health care professional behavior of nurses and nursing students when compared with no instruction [15]. More recently, the results of a pilot randomized controlled trial in medical students showed that an e-learning course was successful in enhancing mental health first-aid intentions in medical students, suggesting the potential of the e-learning course to improve mental health first-aid skills [16]. Furthermore, positive results in cost-effectiveness have made e-learning a more popular tool for therapists in mental health [17]. The University of Oxford has developed a Web-centered training for enhanced cognitive behavioral therapy for eating disorders, which successfully trained a large number of therapists [18]; for example, of the 102 therapists who commenced the training program, more than 80% completed the training, and their scores increased substantially on the validated measure of competence [17].

This Study

Suicide is known to be a complex issue that requires a range of prevention initiatives and methods of evaluation [19]. In the Netherlands, mental health institutions are joining forces to make e-learning for mental health care professionals (in training) on therapeutic skills widely available [20]. As part of a proven effective e-learning–supported Train-the-Trainer intervention named Professionals in Training to STOP (PITSTOP) suicide, an e-learning module was developed to appropriately discuss suicidality in a professional context and offered in conjunction with face-to-face training [21-23]. Considering the positive results of PITSTOP suicide on professionals and the benefits of e-learning in mental health education [24,25], this study aimed to determine the effectiveness of the singular use of the e-learning module on knowledge of suicide prevention, provider's confidence, and adherence to the Dutch guideline on the assessment of suicidal behavior [26] in undergraduate psychology students.

Methods

Design and Procedure

A randomized controlled trial was conducted among the third- and fourth-year undergraduate clinical (neuro-) psychology students of the Vrije Universiteit (VU) University in Amsterdam, The Netherlands, who were fluent in Dutch. Students at that particular stage in their curriculum were deemed to be eligible to follow an e-learning module on suicidal behavior because they would be preparing for their internship and their professional career as a health care professional. They were recruited via the student administration office. All participants were informed about the study and provided online informed consent. The study was approved by the ethical committee of the Department of Clinical Psychology at the VU University.

Baseline (T0) questionnaires were sent to each participant. Subsequently, participants were randomized to either the intervention or the waitlist control condition using the randomize subset option in Qualtrics. In the intervention condition, participants received both a message in Qualtrics and an email with the link and the log-in code for the e-learning module. Follow-up questionnaires were sent 1 and 3 months after the baseline questionnaires (T1 and T2). The participants in the waitlist control condition received a message via Qualtrics, thanking them for the completion of the first questionnaire (T0) and informing them about a follow-up questionnaire after 1 month. After completing the T1 follow-up, participants in the waitlist control group also received access to the module, with a final follow-up at T2. All participants were blind to their condition. As an incentive to finish the module, all participants could request a certificate when they finished at least two assessments and had followed the e-learning module for at least half an hour.

Intervention

The e-learning module was originally developed to support a face-to-face training called PITSTOP suicide [21]. The content of both the face-to-face training and the e-learning module was based on the Dutch multidisciplinary guideline on the assessment and treatment of suicidal behavior [26]. The core of the module consisted of 5 videos in which experienced nurses, psychologists, and psychiatrists interacted with different patients with suicidal tendencies, played by actors, to teach the guideline recommendations. The patients were of various ages, gender, and diagnostic categories and displayed various prototypical suicidal symptoms, cognitions, and interaction problems. In designing the video content, the dialogues were purposely unscripted to enable more realistic scenes and to prevent the professionals from acting. In addition, the videos included vignettes, guideline topics, and recommendations that were explained by experts on the topic. The psychiatrists, psychologists, and nurses were selected from the clinical staff of departments participating in the PITSTOP study to act as a role model in the module. During the PITSTOP study, trainees had personalized access to the e-learning module that could be viewed repeatedly. The total running time of the module was 60 min.

Outcome Measures

To assess *guideline adherence*, students rated 5 video vignettes of 30 seconds, in which experienced nurses, psychologists, and psychiatrists interact with suicidal characters, played by actors, on the likelihood that they would respond with any of the 25 different interventions on a visual analog scale (ranging from 1 to 100, with 1=very unlikely and 100=very likely). The examples of interventions are “Ask whether the patient thinks about suicide” and “Ask how hopeless the patient is feeling.” At T0, T1, and T2, participants rated the same vignettes. The mean item score of the 125 items (25 items × 5 vignettes) was used as an estimate for guideline adherence, which ranged from 0 to 100, with higher scores representing stronger guideline adherence. The internal consistency of the guideline adherence scale appeared to be excellent (Cronbach alpha=.96) in this sample.

The *knowledge of suicidal behavior* was measured by the 7-item subscale self-evaluation of knowledge on suicidal behavior of the 14-item Question-Persuade-Refer questionnaire [27]. The students were asked to rate the extent to which their knowledge increased on items including “Suicide warning signs,” “How to ask someone who may be suicidal,” and “Persuading someone to get help” on a 5-point scale from 1 (very little) to 5 (a lot). Cronbach alpha was .86, reflecting a good internal consistency.

The *provider’s confidence* was calculated by summing the scores of the 2 items “I am confident in my ability to successfully assess suicidal patients” and “I am confident in my ability to successfully treat suicidal patients” [28]. The response options were strongly disagree, disagree, neutral, agree, and strongly agree (ranging from 1 to 5).

For the *evaluation of the e-learning module*, participants were asked regarding the extent to which they agreed with the following statements (range 1-10), rating from totally disagree to totally agree: “I learned a lot about prevention of suicide,” “The module is a good preparation for my internship/future/job as psychologist,” “I would recommend the module to my colleagues and fellow students,” “I feel confident dealing with people with suicidal thoughts,” and “I appreciate the e-learning module.” The mean score of the 5 items was used to express the evaluation of the e-learning.

Sample Size

To calculate the sample size, we used the effect size (Cohen *d*) of data from the PITSTOP suicide study on provider’s confidence. The effect size in PITSTOP suicide study was 0.5. To be able to detect this effect size, assuming an alpha of .05 and the statistical power of 1−beta=.80, we set the total number of participants to be included to 128. To allow for attrition, more than 128 participants were included.

Analysis

Baseline characteristics were compared between groups using independent sample *t* tests and chi-square tests. A missing values analysis was conducted to assess the patterns of missing values. Data were imputed using multiple imputation with 10 imputations and 100 iterations, using the *mice*-package [29]. To assess the effect of the module on the levels of guideline adherence, self-evaluation of knowledge, and provider’s confidence, we performed linear regression analyses with scores at T1 as outcome, scores at baseline as covariate, and condition as between-subjects variable.

To assess the follow-up effect of the module (ie, when both conditions had received the module), we performed paired sample *t* tests between T1 and T2 separately for each condition on the completers-only data as a sensitivity analysis. All analyses were performed with SPSS Statistics 25.0 (IBM Corp, Armonk, New York, 2019) and R version 3.5.0 (R Core Team, Vienna, Austria, 2018).

Results

Sample Characteristics

T0 were filled in by 398 participants, from which 211 were randomized to the intervention group and 187 to the waitlist control group. Participants in the intervention group reported higher levels of self-evaluated knowledge (t_{396}=2.1; *P*=.03), and in the waitlist control group, more participants had already completed their practical clinical internship ($\chi^2_{1,398}$=4.5; *P*=.04). No difference regarding other baseline characteristics was noted in the groups (see Table 1).

Table 1. Group differences at baseline and at 1 month and 3 months after baseline on characteristics and outcome measures (N=398).

Characteristics	Intervention group (n=211)	Waitlist control group (n=187)	*P* value
Female gender, n (%)	180 (85.3)	156 (83.4)	.68
Age (years), mean (SD)	22.1 (4.0)	22.1 (3.0)	.99
Completed internship, yes, n (%)	58 (27.5)	70 (37.4)	.04[a]
T0[b] Guideline adherence, mean (SD)	57.4 (11.5)	58.9 (11.4)	.19
T1[c] Guideline adherence, mean (SD)	62.1 (15.6)	59.8 (14.7)	<.001[a]
T2[d] Guideline adherence, mean (SD)	62.0 (13.4)	63.7 (10.0)	.47
T0 Self-evaluation of knowledge, mean (SD)	17.3 (4.6)	16.3 (4.6)	.03[a]
T1 Self-evaluation of knowledge, mean (SD)	22.3 (4.6)	16.4 (5.5)	<.001[a]
T2 Self-evaluation of knowledge, mean (SD)	22.9 (3.6)	22.1 (3.9)	.26
T0 Provider's confidence, mean (SD)	5.1 (1.8)	5.0 (1.7)	.61
T1 Provider's confidence, mean (SD)	6.5 (1.7)	4.6 (1.9)	<.001[a]
T2 Provider's confidence, mean (SD)	6.5 (1.5)	6.0 (1.7)	.23

[a] *P* values<.05 were considered significant.

[b] T0: baseline.

[c] T1: 1 month after baseline.

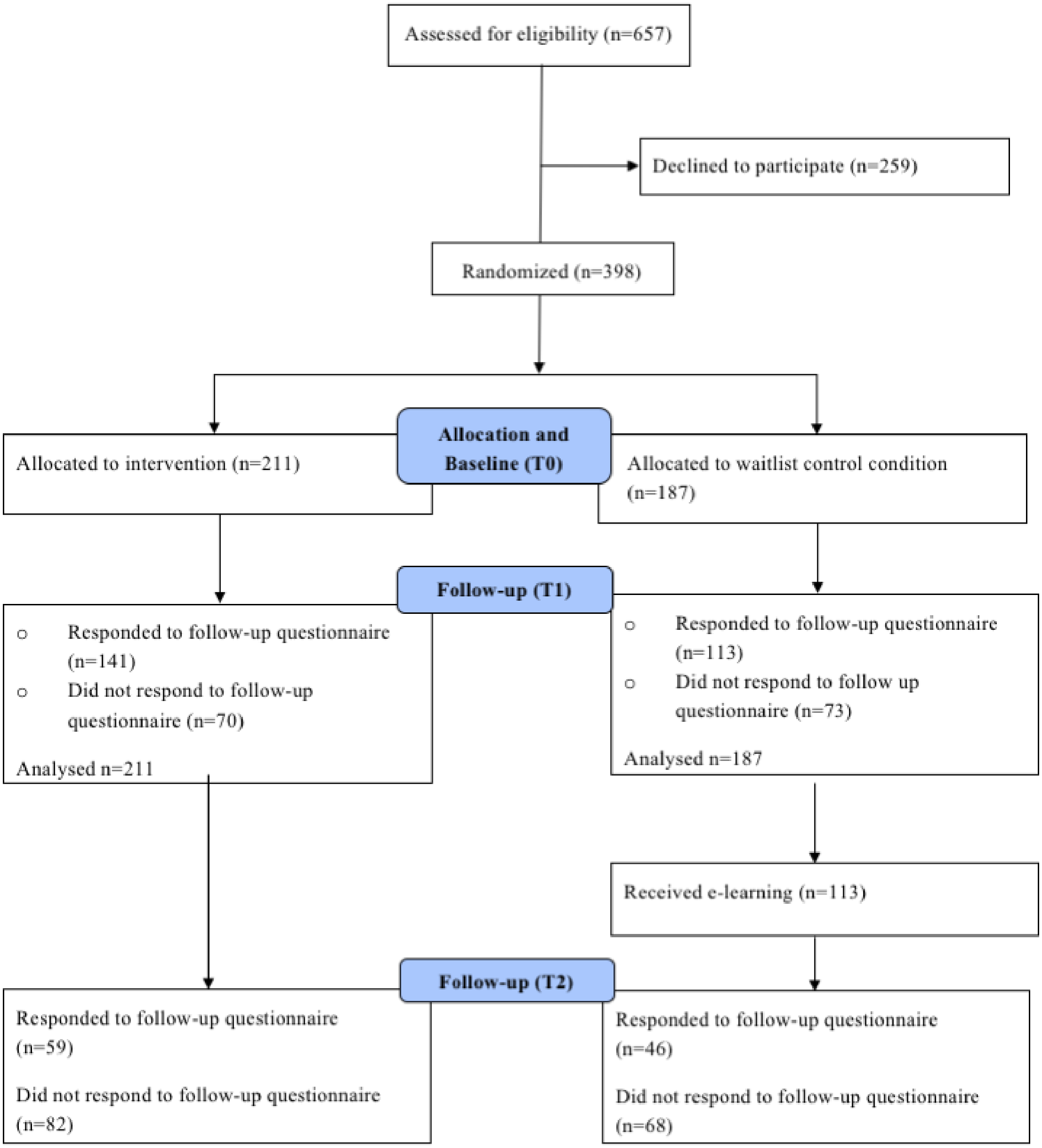
[d] T2: 3 months after baseline.

Dropout and Missing Data

Figure 1 shows the flow of students through the trial. Of the 211 intervention group participants, 141 (66.8%) completed the T1 follow-up, and 59 (28%) completed the T2 follow-up. In the waitlist control group (n=187), 113 participants (60.5%) completed the T1 follow-up. After T1, the participants in the waitlist control condition were offered the intervention, of which 46 (25%) used the e-learning and completed the T2 follow-up.

Dropout rates at T1 in the intervention condition were higher than those in the waitlist control condition and were comparable in both conditions at T2. Values at T1 and T2 were not missing at random according to the Little's missing completely at random test (χ^2_{11}=22.8; *P*=.02). Baseline characteristics were used to predict missing values at follow-up. Completers were younger than noncompleters at T1 (t_{180}=–2.4; *P*=.02) and T2 (t_{330}=–2.2; *P*=.026). Completers showed higher levels of provider's confidence than noncompleters at T1 (t_{301}=2.2; *P*=.03). For all other baseline characteristics, noncompleters did not differ from completers (all *P* values>.05).

Figure 1. Flow of students through the trial. T0: baseline; T1: 1 month after baseline; T2: 3 months after baseline.



Imputed Data: Effect of Module on Guideline Adherence, Confidence, and Knowledge

After receiving the e-module (T1), participants in the intervention group reported higher levels of self-evaluated knowledge (beta=5.3; SE=0.43; *d*=1.6), guideline adherence (beta=3.5; SE=1.0; *d*=0.15), and provider's confidence (beta=1.7; SE=0.17; *d*=1.1) than those in the waitlist control group. Baseline levels of knowledge, confidence, and guideline adherence were included as covariates in the regression analyses.

Completer Analysis

When completers-only data (intervention group: n=141 and waitlist control group: n=113) was used at T1, the intervention group scored higher on guideline adherence (beta=3.5; 95% CI 1.7-5.8; *d*=0.5), knowledge (beta=5.3; 95% CI 4.5-6.1; *d*=1.4), and confidence (beta=1.7; 95% CI 1.3-2.0; *d*=1.1) than the waitlist control group. Provider's confidence in dealing with suicidal behavior (t_{140}=9.9; *P*<.001), guideline adherence (t_{140}=6.19; *P*<.001), and self-reported knowledge (t_{140}=15.42; *P*<.001) significantly increased in the participants in the intervention group after completion of the e-learning module.

Comparison of the scores at T1 and T2 follow-up that were made using completers-only data showed that levels of knowledge, guideline adherence, and confidence within the intervention group stayed constant (all *P* values>.05), and the levels of the outcome variables, such as knowledge (t_{45}=7.6; *P*<.001), guideline adherence (t_{45}=2.5; *P*<.018), and provider's confidence (t_{45}=2.5; *P*=.002), within the waitlist control group improved significantly after receiving the e-learning module.

Evaluation of the Module by Completers

Participants who completed the intervention (N=102) filled in the evaluation questionnaires at T2, indicating the extent to which they agreed with the statements evaluating the e-learning module. The results show evaluation scores ranging from 6.2 for the statement "I feel confident dealing with people with suicidal thoughts” (SD 1.9) to 7.5 for the statement “I appreciate the e-learning module” (SD 1.5). In addition, the participants rated the other statements in a moderately positive manner, for example, “I learned a lot about prevention of suicide” (mean 6.8, SD 1.4), “The module is a good preparation for my internship/future/job as psychologist” (mean 6.9, SD 1.4), and “I would recommend the module to my colleagues and fellow students” (mean 7.1, SD 1.5).

Discussion

Principal Findings

This study aimed to test the effectiveness of a suicide e-learning module in undergraduate students with respect to the knowledge of suicide prevention, provider’s confidence to have a dialogue about suicide, and adherence to the national guidelines on the assessment of suicidal behavior [26]. One month after completing the e-learning module, the students in the intervention condition reported feeling more confident and knowledgeable compared with those in the waitlist control group who did not have access to the e-learning module. Completers in the intervention condition demonstrated better guideline adherence, knowledge, and provider’s confidence than waitlist controls. The learning effects of the e-learning module were maintained at the 3-month follow-up. These results were replicated in participants in the waitlist control condition who completed the e-learning module after T1. The results were comparable with the improvement in provider’s confidence, guideline adherence, and self-reported knowledge in mental health care professionals who received both e-learning and face-to-face training [22,24]. These findings are surprising as well as encouraging because we expected smaller effect sizes in students compared with professionals owing to the intense 1-day face-to-face training that accompanied the e-learning for the professionals [23]. Owing to less clinical experience, the baseline skills and knowledge level of students were lower than that of the professionals and may have provided more room for improvement. Hence, the effects of additional face-to-face training in this group of undergraduate students above those of the e-learning module are worth investigating.

Furthermore, the results were also comparable with those of a study evaluating an e-learning module on suicide prevention in mental health providers in the United States [30]. In this study, the effects of e-learning were similar to that of an in-person training on suicide prevention. The effect sizes of guideline adherence were considered small; however, in this study, approximately 10% change in guideline adherence, provider’s confidence, and knowledge was found, which is consistent with other studies in general medicine and psychiatry on the effect of educative interventions that show an average of 10% improvement [31,32].

Strengths and Limitations

The randomized controlled design with follow-up is rare in this field of research and can be considered a strength in this study [33]. However, dropout rate in our study, although comparable with a previous study among students [16] and yet still higher than in a study involving professionals [22], was a significant limitation and may represent diminished student satisfaction regarding e-learning [34]. In addition, differential dropout occurred across conditions, possibly because of motivational reasons. Furthermore, the evaluations of guideline adherence, confidence, and knowledge were self-reported, which are subject to the effects of social desirability and demand characteristics, although fairly reliable [35,36]. To get a more objective outcome, one could use role-plays in which a participant interacts with a patient with suicidal tendencies; however, this is much more time consuming. Although this study showed the effectiveness of e-learning in a waitlist control design, its relative effectiveness to alternative research-validated suicide prevention training programs [37] remains unclear and worth studying, especially considering the potential cost- and resource-efficiency of e-learning. Finally, it remains important to question how well the results obtained in a volunteer student sample generalize to working professionals required to take the course. However, as mentioned previously, similar results were found for mental health professionals in our previous study [23], indicating promising generalizability for the workforce.

Implications and Future Research

E-learning modules, as the one used in this study, may be a beneficial, accessible way to provide training in suicide prevention skills to both students and professionals [38]. We propose to use e-learning modules in training suicide prevention skills in a wide range of higher education disciplines, such as curricula in nursing, social work, psychology, and psychiatry, to improve the knowledge and skills of clinicians-in-training regarding suicide prevention on a greater scale and consequently improve the care of patients with suicidal thoughts. To evaluate the transfer of knowledge and skills, and competencies of the clinicians (in training) to deal with clients’ suicidal behavior and subsequently reduce suicidality rates, future studies should include (objective) measures for clinician behavior. In addition, careful logging of content exposure and participant adherence to the program is advised for future studies to evaluate the extent to which the effects are attributable to the actual intervention as well as to evaluate the acceptability and feasibility of the intervention for future implementation. Because evidence of the cost-effectiveness of Web-based education in students is still lacking [14], future studies on the benefits of e-learning should consider (the reduction in) costs of personnel, education, and implementation to evaluate the cost-effectiveness. This study, with a randomized design and a feasible sample size of undergraduate students, provides first evidence of the positive effects of acquainting students on a large scale with the suicide prevention guidelines by means of an e-learning module. An e-learning module on the prevention of suicide could be an effective first step toward the improvement of clinical skill knowledge [39]. The learning outcomes of a stand-alone module were found to be similar to those of a training that combined e-learning with a face-to-face training, with the advantages of flexibility and low costs [15,30]. Furthermore, the students found the effects of the module to be reasonably positive; they believed that it prepared them well for their internship or job, and they were willing to recommend the module to colleagues and fellow students.

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Authors' Contributions

DdB designed the e-learning modules. DdB and RMFK performed the study. MLJK conducted all analyses and drafted the manuscript. JM, MS, and AJFMK contributed to writing of the manuscript. All authors contributed to the execution of the study and approved the final draft.

Conflicts of Interest

None declared.

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Abbreviations

e-learning: electronic learning
PITSTOP: Professionals in Training to STOP
T0: baseline
T1: 1 month after baseline
T2: 3 months after baseline
VU: Vrije Universiteit

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Original Paper

Tracking and Predicting Depressive Symptoms of Adolescents Using Smartphone-Based Self-Reports, Parental Evaluations, and Passive Phone Sensor Data: Development and Usability Study

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Abstract

Background: Depression carries significant financial, medical, and emotional burden on modern society. Various proof-of-concept studies have highlighted how apps can link dynamic mental health status changes to fluctuations in smartphone usage in adult patients with major depressive disorder (MDD). However, the use of such apps to monitor adolescents remains a challenge.

Objective: This study aimed to investigate whether smartphone apps are useful in evaluating and monitoring depression symptoms in a clinically depressed adolescent population compared with the following gold-standard clinical psychometric instruments: Patient Health Questionnaire (PHQ-9), Hamilton Rating Scale for Depression (HAM-D), and Hamilton Anxiety Rating Scale (HAM-A).

Methods: We recruited 13 families with adolescent patients diagnosed with MDD with or without comorbid anxiety disorder. Over an 8-week period, daily self-reported moods and smartphone sensor data were collected by using the *Smartphone- and OnLine usage–based eValuation for Depression* (SOLVD) app. The evaluations from teens' parents were also collected. Baseline depression and anxiety symptoms were measured biweekly using PHQ-9, HAM-D, and HAM-A.

Results: We observed a significant correlation between the self-evaluated mood averaged over a 2-week period and the biweekly psychometric scores from PHQ-9, HAM-D, and HAM-A ($0.45 \leq |r| \leq 0.63$; *P*=.009, *P*=.01, and *P*=.003, respectively). The daily steps taken, SMS frequency, and average call duration were also highly correlated with clinical scores ($0.44 \leq |r| \leq 0.72$; all *P*<.05). By combining self-evaluations and smartphone sensor data of the teens, we could predict the PHQ-9 score with an accuracy of 88% (23.77/27). When adding the evaluations from the teens' parents, the prediction accuracy was further increased to 90% (24.35/27).

Conclusions: Smartphone apps such as SOLVD represent a useful way to monitor depressive symptoms in clinically depressed adolescents, and these apps correlate well with current gold-standard psychometric instruments. This is a first study of its kind that was conducted on the adolescent population, and it included inputs from both teens and their parents as observers. The results are preliminary because of the small sample size, and we plan to expand the study to a larger population.

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KEYWORDS

SOLVD-Teen and SOLVD-Parent App; adolescent depression; smartphone monitoring; self-evaluation; parental input; sensory data

Introduction

Background

Depression has a global lifetime prevalence of 28.8% and carries significant financial, medical, and emotional burden on modern society [1,2]. The World Health Organization (WHO) estimates that depression alone accounts for 4.3% of the global burden of disease and is the largest single cause of disability worldwide (according to the WHO Action Plan 2013-2020 [3]). However, a key challenge in the care of persons with depression is that there is often no quantified information about the psychological status of the individual between sporadic clinical psychometric evaluations every few months. Thus, the dynamic changes in an individual's mental health status remain invisible to health care systems.

Several proof-of-concept studies have highlighted activity changes captured by smartphone sensors, and the usage patterns are associated with depressive symptoms in adult patients with major depressive disorder (MDD) [4,5]. Higher degrees of depression are linked to reduced contact with one's social network, shorter text messages, reduced duration of calls, and less variability in geospatial activity [6-9]. The same observations were reproduced in younger adults (aged 19-30 years) [10], showing that changes in daily stress levels in young adults aged 19 to 30 years were associated with changes in geospatial activity, sleep duration (obtained by proxy from phone sensors), and sensor-derived speech duration. A pioneer study was conducted by co-designed smartphone apps to monitor mood symptoms for the youth with major depression, suicidal ideation, and self-harm [11]. However, to date, studies on smartphone-based depression monitoring are still limited in the context of teenagers.

Objective and Results

In this paper, we report the results from a *Smartphone- and OnLine usage–based eValuation for Depression* (SOLVD)-Teen trial with the aim to quantify the use of smartphones in monitoring depression in a clinically depressed adolescent population. We had two main hypotheses. First, we hypothesized that a combination of smartphone sensors' usage and patient self-reports of daily mood can be predictive of depressive states when compared with standard clinical psychometric instruments such as Patient Health Questionnaire-9 (PHQ-9), Hamilton Rating Scale for Depression (HAM-D), and Hamilton Anxiety Rating Scale (HAM-A). Second, parental reports about the teen's mood can serve as an important dimension in tracking and predicting the teen's depressive status as the parents are often involved in the care of their teen and hence can potentially serve as a human *sensor* of their teen's mood.

We found an affirmative answer to both our hypotheses. Specifically, our key findings are as follows. First, smartphone sensors (GPS and step count) provide coarse information about user mobility, and smartphone usage (phone calls and text messages) provides coarse information about communication patterns. When the above information is combined with daily user self-reports on mood, it can be used to accurately predict future psychometric scores; the details are presented in the Results section. Second, parental reports about a teen's mood are correlated with the teen's baseline psychometric scores, and thus, they provide a new dimension for tracking a teen's mental status. This is an important finding, especially when the teen is not compliant to recording their mood status, and it could provide a new dimension in clinical care by recruiting parents. Third, if we combine parental reports with the teen's smartphone sensor and usage data, then PHQ-9 can be predicted even more accurately. Thus, parental data provide new *useful* information and make the predictors more accurate. It should be noted that none of our methods rely on the content of messages or calls but only aggregated statistics, for example, frequencies and durations.

Related Work

Although our results are a promising step toward developing new tools and methods for managing adolescent conditions, the usage of apps to monitor adolescents remains a challenge. Even though teenagers have high rates of smartphone use, they also represent a vulnerable population with a high degree of impulsivity and frequent reports of suicidal ideation; these factors may actually lead to exclusion of more than half depressed teenagers from traditional pharmaceutical trials [12]. In a nationally representative sample of adolescents in the United States, about 22% of teenagers had a mental illness with significant distress, and 40% of those meeting the criteria for one disorder also met the criteria for another class of disorders (eg, anxiety and mood) [1]. Furthermore, teenage years represent the time when many mental disorders start; therefore, a lack of diagnostic clarity is noted in many clinical cases. The onset of anxiety and depression with some mood lability may indicate bipolar disorder [13], and there is a very high comorbidity between anxiety and depressive symptoms in childhood, adolescent, and early adulthood phases [14]. The diagnostic dilemmas of adolescent psychiatry also include the question of whether suicidal ideation due to antidepressant use is a result of subsyndromal undiagnosed bipolar disorder [15].

It should be noted that the treatment of anxiety and depression in adolescents is crucial to ensure healthy life trajectories. In a meta-analysis of studies encompassing more than 762,000 patients, the presence of a childhood or an adolescent mental health disorder significantly increased the odds of alcohol and substance use disorders later in life [16]. The Finnish Health 2011 longitudinal study [17] also shows that young adults with mental health disorders, especially those diagnosed before adulthood, have poorer quality of life and need more support to achieve academic goals.

To date, several apps are available for download, but they have not undergone rigorous research or clinical evaluations [18]. Grist et al [19], in a survey of 775 adolescent girls, found that the use of mental health apps occurred infrequently, no more than 15%, reinforcing that although adolescents are avid technology users, directed use for mental health improvement has not been tested or widely publicized. Thus, it is important to find ways that do *not* require constant user engagement. Toward that end, the SOLVD-Teen approach of passive logging of sensors and usage from teens' phones and active input from parents could provide a new way of leveraging smartphones, especially passive sensor data.

Methods

Smartphone- and OnLine Usage–Based eValuation for Depression App Design

We designed the SOLVD apps with the aim of converting a smartphone to a quantitative *mental health sensor*. The design goal was to have a simple user interface while collecting context-rich sensory data automatically in the background and protecting user privacy. As we are not allowed to continuously track user location and log smartphone usage data in the background on the Apple iOS platform, the SOLVD apps only support Android smartphones.

The SOLVD apps that were targeted at the adolescent population consisted of 2 pairing apps: the SOLVD-Teen app and the SOLVD-Parent app. Both apps have a user-facing module that collects users' active responses to ecological momentary assessment (EMA) questions, and a background mobile logger that records smartphone sensor and usage data. The user-facing module sends out a notification daily around 8 PM to collect users' self-evaluations of their mood and anxiety level. The users submit their responses by sliding a bar, and the results are converted to a numerical score between 0 and 100. Meanwhile, the Mobile Logger continuously runs in the background and collects sensor and usage data, including accelerometer, GPS, steps, call log, text messages, screen on and off status, and ambient light intensity. The data are first stored locally and then automatically uploaded to a remote server when the phone is in an idle state and the Wi-Fi is connected. To protect user privacy, we used one-way MD5 hashing on the fly during the data-logging stage to encrypt sensitive information such as phone numbers and email addresses, thus guaranteeing that the user identity is never recorded either locally or remotely. Figure 1 shows the screenshots of the SOLVD-Teen and SOLVD-Parent apps.

Figure 1. Screenshots of the *Smartphone- and OnLine usage–based eValuation for Depression* (SOLVD)-Teen (left) and SOLVD-Parent (right) apps. The user input is converted to a numerical score between 0 and 100. The frontend of the SOLVD-Parent app is modified to capture both the parents' self-evaluations and their perceived well-being of their kids.

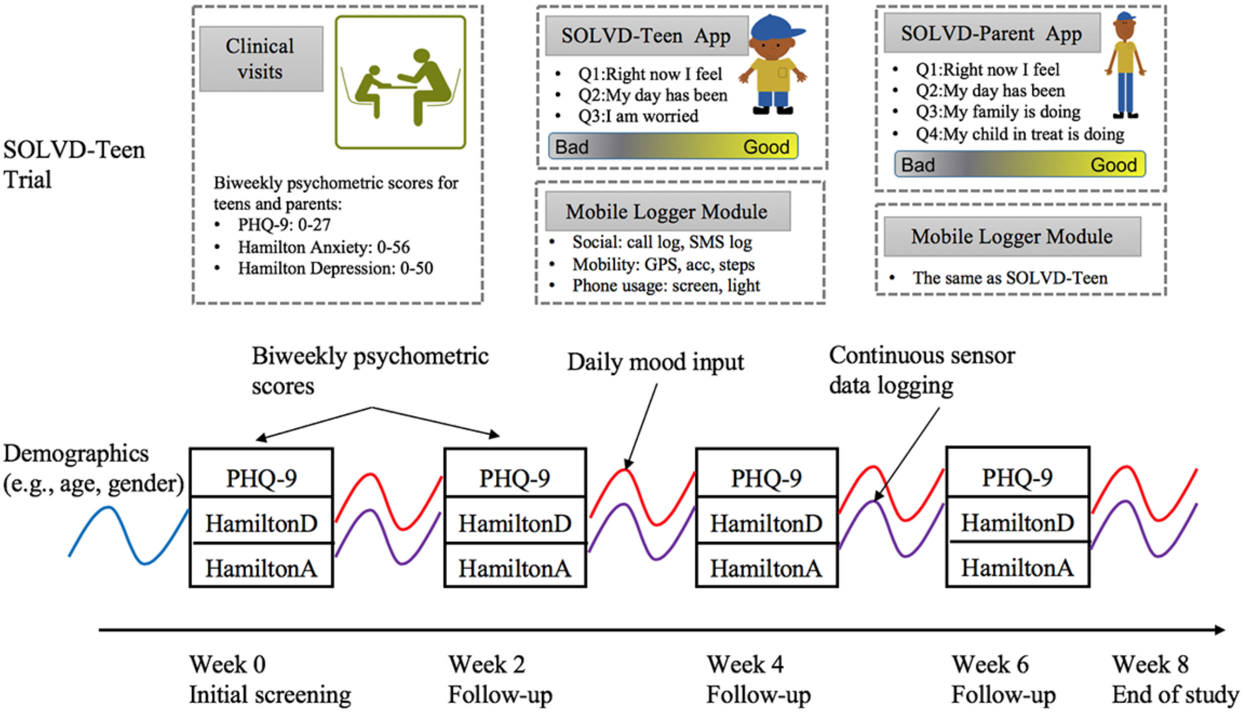
Study Design

The SOLVD-Teen study was an extension of the SOLVD pilot trial [9], which established a correlation between clinician-rated measures, self-rated measures, and sensor-based app measures for depressed adult patients. The SOLVD-Teen trial was designed for adolescent patients together with at least one parent. Each subject or family was required to enroll in the study for 8 weeks and use the SOLVD-Teen app to evaluate the utility of smartphones for the evaluation and monitoring of MDD. The study was approved by the institutional review boards (IRB) of Baylor College of Medicine, Rice University, and Harris Health Systems.

We collected 3 forms of data: (1) biweekly in-clinic psychometric scores from PHQ-9, HAM-A, and HAM-D; (2) daily self-inputs submitted via the SOLVD app; (3) smartphone sensor and usage data, including GPS, steps, accelerometer, call log, text messages, screen status, and ambient light intensity, by running an Android logger continuously in the background. For the teen trial, we expanded the data collection protocol and included the teens' parents in the study. Their parents used the SOLVD-Parent app to submit their self-inputs and log smartphone background data, and they also attended the biweekly clinical assessment. Figure 2 details the data collection protocol and the timeline for the trial.

During the initial visit, the subjects signed their informed consent forms after an explanation of how their phone and sensor data would be collected, stored, and deidentified. Subjects also completed the Mini International Neuropsychiatric Interview (MINI) to confirm a diagnosis of MDD. Standard clinical psychometric instruments such as PHQ-9, HAM-D, and HAM-A were administered to ascertain baseline depression and anxiety symptoms. Subjects were directed to download the SOLVD-Teen or SOLVD-Parent apps on their personal smartphones with the assistance of a research clinician.

Figure 2. Study design, data collection protocol, and study timeline for the *Smartphone- and OnLine usage–based eValuation for Depression* (SOLVD)-Teen trial. Both SOLVD-Teen and SOLVD-Parent apps have a user-facing module and a background mobile logger. Each subject enrolled in the study for 8 weeks.



For the following weeks, all subjects utilized their personal smartphones to run the SOLVD apps and received standard outpatient treatment as usual over the 8-week duration of the study. During this period, patients were also evaluated biweekly by a research clinician to assess for depression and anxiety symptoms using the HAM-D, HAM-A, and PHQ-9 scales. The clinician was blinded to the smartphone data. The patients were compensated for each of these 4 visits.

Recruitment

The subjects for the SOLVD-Teen trial were recruited from the outpatient psychiatry clinic at Ben Taub Hospital, Harris Health System, in Houston, Texas, between December 2016 and February 2017. The subjects were recruited from an intensive therapy program, *AIM*, an 8-week intensive individual and group therapy with the patients with depression and their parents. The inclusion criteria included both English- and Spanish-speaking adolescent patients aged 12 to 17 years of both genders with the diagnosis of MDD as confirmed by the MINI. The exclusion criteria included patients with substance use, bipolar disorder, severe conduct disorder, and autism spectrum disorders. All patients were receiving pharmacological treatment at the time of the study, and no medication regimen changes were made through the duration. The study was approved by the IRB of Rice University (IRB number FY2017-241) and Baylor College of Medicine (IRB number H-36157).

Feature Extraction and Statistical Analysis

The sensor data generated by the SOLVD apps varied in sampling rate and duty cycle. To correlate with the biweekly psychometric scores, we extracted various features on a daily basis, which were related to mobility, social interactions, and daily living context. The details for each sensor type and the extracted features are explained below.

Mobility

To understand the association between depressive symptoms and the mobility of the subjects, we had configured the SOLVD-Teen app to track both the step count and the GPS location of its user. Then, we extracted multiple features (essentially, statistical summarizations of the data) to capture the activity level and daily trajectory of the subjects. The details are listed below.

Step Counter

When each step was detected by the step counter, we recorded the timestamp associated with that step. Then, we computed the total number of steps during nighttime (11 PM-7 AM) and daytime (7 AM-11 PM) per day.

GPS Location

We logged each GPS data point when the displacement from the last point is larger than 5 m or when the time elapsed from the last point is longer than 5 s. For the data points collected, first, we estimated the moving speed at each location and determined whether each data point belonged to a stationary state (speed<0.2 m/s) or transition state (speed≥1 m/s). Then for data points in stationary states, we used K-means clustering to group all data points into location clusters. The K-means clustering identifies the points around which different data points are clustered, allowing for summarization of the whole data by fewer key points. As we had no prior information regarding the frequently visited places, we started with 1 cluster and gradually increased the number of clusters until all points fell within 500 m from a cluster center. Next, for data points in transitional states, we categorized the transportation modes into *automobile*

(7-45 m/s), *walking* (1-2 m/s), and *unknown* based on the moving speed. Finally, we extracted the total distance, transition time, location variance, number of frequently visited places, normalized entropy, and home stay for each subject on a daily basis [20-22]. The speed thresholds are manually chosen, and the definition for each feature is listed below:

1. Total distance, which is defined as the total distance in kilometers traveled by a participant per day, was computed by accumulating the geodesic distance between 2 individual points using the Vincenty formula [23,24].
2. Transition time, which is defined as the duration of each transportation mode (automobile, walking, and unknown) categorized by the moving speed.
3. Location variance, which is defined as the logarithm of sum of the statistical variances of the longitude and latitude for each stationary point, as in Equation (1) in Figure 3. It measures the variability in each subject's GPS location per day. A higher location variance is related to higher mobility.
4. Number of frequently visited places per day, which is defined as the number of frequently visited places for each day, out of all the frequently visited places identified by the K-means algorithm over the entire study period.
5. Normalized entropy is defined in Equation (2) in Figure 3, where i=1..., N represented a frequently visited place out of the N clusters, and was the percentage of time that the participant spent at place i. It measures the uniformity of the time the participant spent at the frequently visited places each day. The higher the entropy, the more uniformly the participant spent time across different places. Conversely, lower entropy indicates more fraction of the time in a fewer places out of the N clusters.

Figure 3. Definition and equations of location variance and normalized entropy.

$$Location\ variance = log(\sigma^2_{latitude} + \sigma^2_{longitude}),$$

$$\sigma^2_{latitude} = \sum_{i=1}^{N}(latitude_i - latitude_{i-1})^2,$$

$$\sigma^2_{longitude} = \sum_{i=1}^{N}(longitide_i - longitude_{i-1})^2 \qquad (1)$$

$$Normalized\ entropy = -\sum_{i=1}^{N} p_i \mathrm{log} p_i \ /\mathrm{log}N \qquad (2)$$

Social Interactions

To study how social interactions are associated with depressive symptoms, we logged the phone calls and text messages of the subjects. Then, we computed different features based on the aggregated statistics to quantify phone-based social interactions, specifically, as follows:

Call Log

For each phone call, we logged its timestamp, phone number, type (incoming, outgoing, and missing), and duration. The phone number was encrypted using one-way MD5 hashing to protect user privacy. For each user, we calculated the number of unique phone call partners per day. We also extracted his or her top-10 most frequent contacts during the study period and computed the total number of phone calls, total call duration, and average call duration with the frequent contacts on a daily basis.

SMS Log

For each text message, we logged its timestamp, phone number (one-way MD5 hashed), type (incoming or, outgoing), and length in the number of characters. Similar to analyzing phone calls, we also extracted the top 10 most frequent contacts during the study period and computed the total number of text messages, total text message length, and average text message length with the 10 frequent contacts on a daily basis.

Daily Living Context

In addition to participant mobility and social interactions, we were also interested in how other daily living contexts were related to depressive symptoms, that is, ambient light intensity that could be an approximation for sleep duration and smartphone screen usage.

Light Sensor

The light sensor reading was logged every 2 min. We calculated the average light intensity for each hour. Then, we selected an empirical threshold τ_I for ambient light intensity to separate the scenario of sleeping with the light off from other scenarios. Then, we computed the total number of hours with average light intensity $<\tau_I$ during nighttime (11 PM-7 AM) per day, which was used as an indicator for sleep duration.

Smartphone Screen Usage

The phone screen status was sampled every 30 seconds. We calculated the percentage of time when the screen was on for each hour, and then computed the number of hours with screen on percentage $>\tau_S$ (we empirically selected 10%) during nighttime (11 PM-7 AM) and daytime (7 AM-11 PM) per day.

After completing the feature extraction, we performed the Pearson correlation analysis between each pair of aggregated self-input data and sensor data over 2 weeks and the biweekly psychometric scores and identified those features that were significantly correlated with a depression state for both the adult and the adolescent populations. For the adolescent population with rich sensor data, we also fitted both linear and nonlinear regressors (in particular, support vector regressor with a polynomial kernel) to predict PHQ-9 scores based on self-inputs and sensor data. The reason for fitting a nonlinear regressor is that, a priori, we have no reason to believe that a more accurate predictor of PHQ-9 is linear.

Results

Subject Demographics and Adherence

For the SOLVD-Teen trial, we recruited 13 teens diagnosed with MDD from Adolescents in Motion (AIM), an intensive program for teenagers that includes multidisciplinary group therapy with the teenagers and family sessions for the parents. For every teenager recruited, one of their parents was recruited with them. The teens included 11 females and 2 males, with an average age of 14.93 (SD 1.59) years. Out of the 13 subjects, 2 were excluded from further analysis as they dropped out of the study within 2 weeks and did not attend any of the follow-up sessions. The remaining 11 teens had an average PHQ-9 score of 12.72 (SD 5.97), with 8 in the normal-to-mild range (PHQ-9 ≤14) and 3 in the moderate-to-severe range (PHQ-9>14).

Their parents included 11 women and 1 man (there was 1 family with 2 teens) and had an average age of 41.48 (SD 9.75) years. In fact, 5 of the 12 parents were also diagnosed with mild depression and 2 showed moderate-to-severe depression. A total of 8 families completed the entire 8-week trial, and the others enrolled in the study between 4 and 6 weeks. The average teens' and parents' compliance to submit daily evaluations through the SOLVD apps was 79.0% (498/630 days) and 95.7% (603/630 days), respectively.

Relationship Between Smartphone Data and Psychometric Scores

We used the pair-wise Pearson coefficient as an indicator of the correlations between teens' self-reports, parental inputs, smartphone sensor data, and clinical psychometric instruments (PHQ-9, HAM-A, and HAM-D). The smartphone sensor data were represented by mobility, social interaction, and living context–related features extracted using methods in Section *Methods-Feature Extraction and Statistical Analysis*. The analysis and the correlations are shown in Figures 4-6.

Figure 4 shows the Pearson correlation coefficient between teens' self-reports, their parents' ratings, and the biweekly psychometric scores (PHQ-9, HAM-D, and HAM-A). From Figure 4, we observed that both teens' and parents' ratings for mood and anxiety level are significantly correlated with psychometric scores, and teens' self-reports have a slightly higher correlation than parental inputs. Therefore, daily responses submitted through a customized smartphone app by either teens or their parents can be used as a reliable approach for monitoring depression.

Figure 5 shows the correlations between mobility and psychometric scores, where mobility is captured by steps taken and daily trajectory. From the figure, we observed that subjects with higher depression scores tend to have lower mobility, as indicated by fewer steps taken. Patients with more severe depression also visit fewer places and have lower location variance, yet they spend time more uniformly across different places, as reflected by higher normalized entropy. Similar results were also reported in previous studies with depressed adult patients, thus further validating our observations [25]. Although the overall interpretation matches our understanding that depression generally reduces mobility, higher entropy does not seem to have a clear interpretation, and thus it needs further investigation.

The correlations between social interactions, other living context, and psychometric scores are shown in Figure 6. The results indicate that a higher depression score is significantly correlated with lower social interaction level, such as shorter phone call durations and fewer text messages. Conversely, there is no significant correlation between other living contexts, that is, ambient light intensity, smartphone screen usage, and psychometric scores. Thus, as expected, communication patterns are affected by depression severity, but our dataset did not indicate any significant patterns regarding screen usage and ambient light intensity, with the latter being a proxy for sleep duration.

Figure 4. Pearson correlation coefficients between self-reports, parental inputs, and psychometric scores for the adolescent patients. On the basis of the significance level, **P*<.1, ***P*<.05, and ****P*<.01. HAM-A: Hamilton Anxiety Rating Scale; HAM-D: Hamilton Rating Scale for Depression; PHQ-9: Patient Health Questionnaire-9.

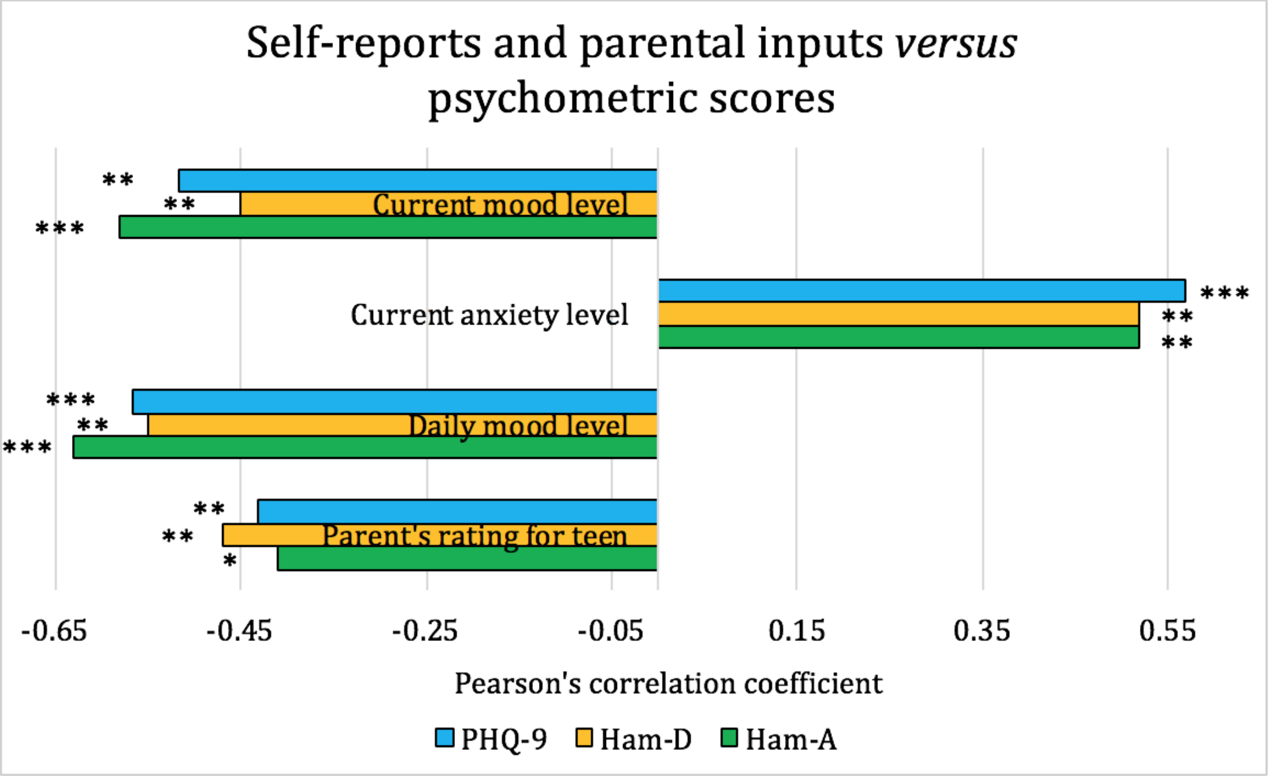


Figure 5. Pearson correlation coefficients between mobility and psychometric scores for the adolescent patients. On the basis of the significance level, **P*<.1, ***P*<.05, and ****P*<.01. HAM-A: Hamilton Anxiety Rating Scale; HAM-D: Hamilton Rating Scale for Depression; PHQ-9: Patient Health Questionnaire-9.

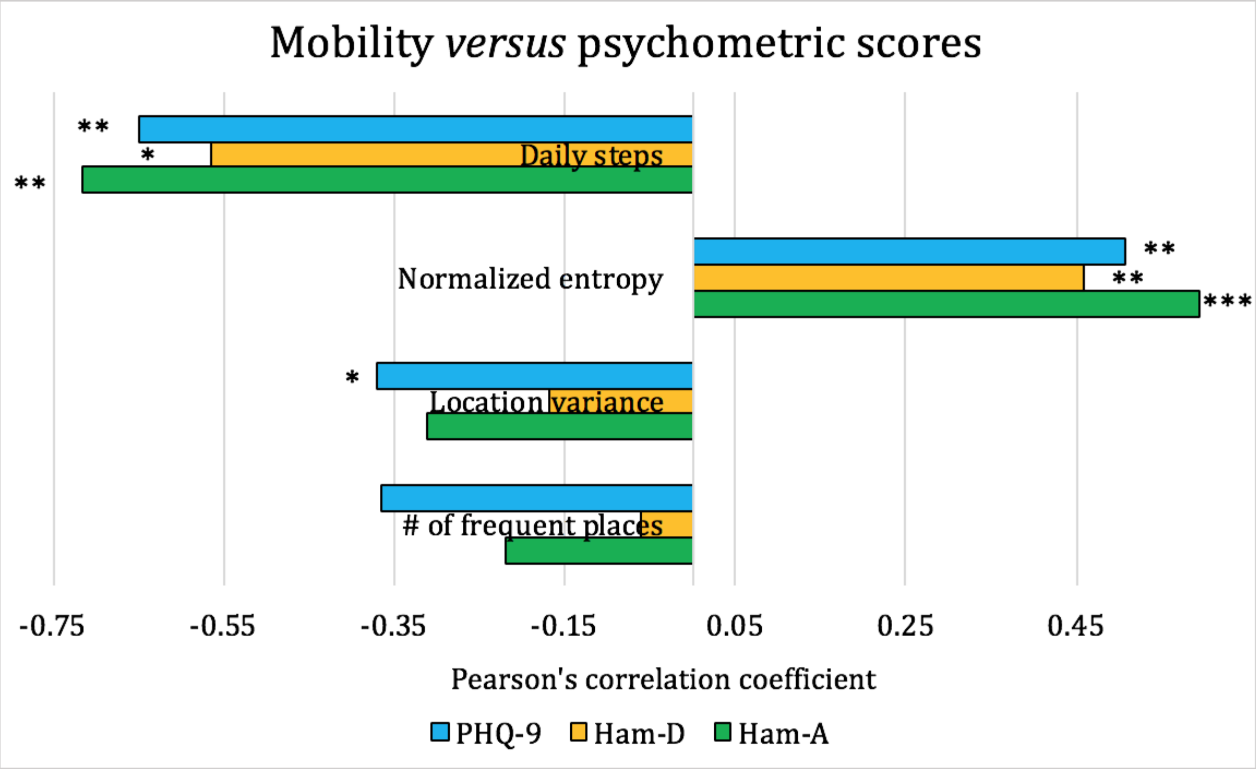
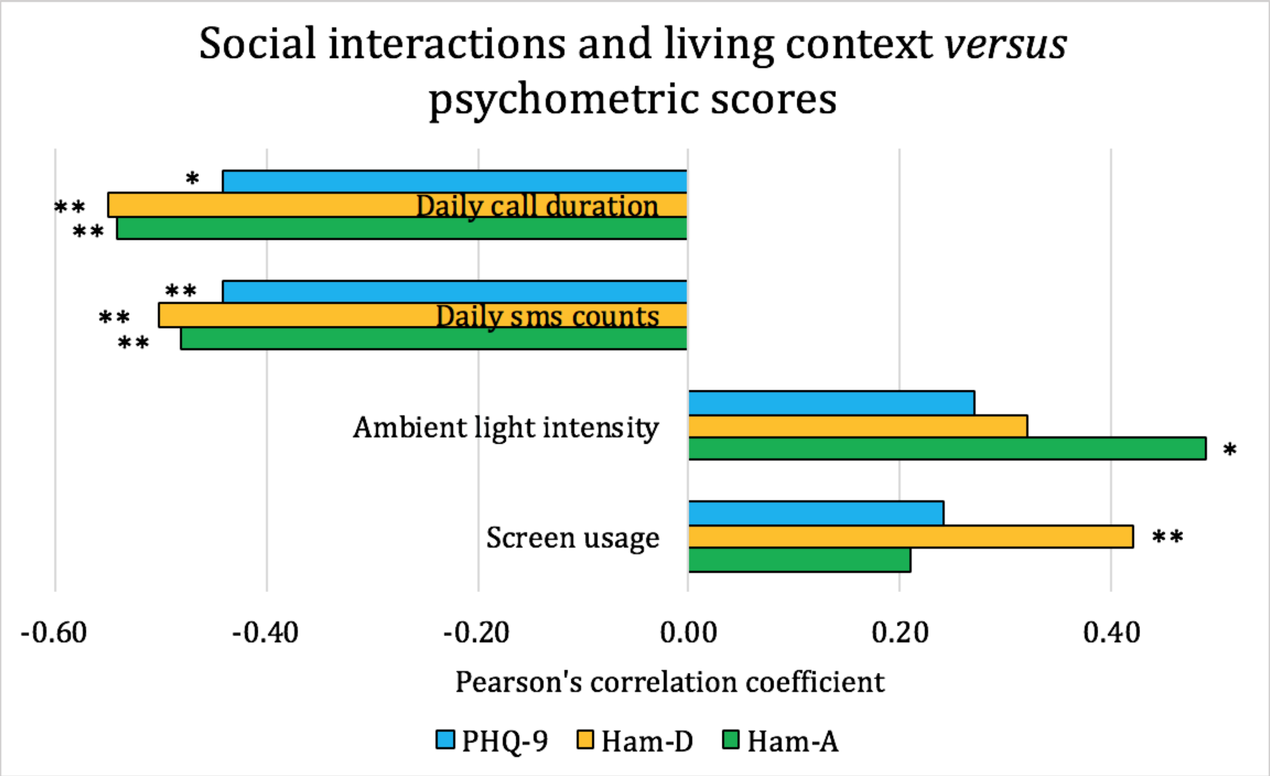


Figure 6. Pearson correlation coefficients between social interactions, living context, and psychometric scores for the adolescent patients. On the basis of the significance level, **P*<.1, ***P*<.05, and ****P*<.01. HAM-A: Hamilton Anxiety Rating Scale; HAM-D: Hamilton Rating Scale for Depression; PHQ-9: Patient Health Questionnaire-9.



Overall, the results indicate a strong correlation between daily smartphone-based EMA questions (ie, teens' self-reports and parental inputs) and clinician-rated psychometric scores. Depressive symptoms assessed by clinical instruments were also significantly correlated with mobility level and social interactions captured by passive smartphone sensor data. However, we did not observe significant correlations between other daily living contexts (ie, ambient light intensity and smartphone screen usage) and depressive symptoms.

Predicting Depression Severity Using Smartphone Data

We further fitted 2 regression models to predict the psychometric scores from the smartphone data, specifically a linear regressor and a support vector regressor with a polynomial kernel. The linear regressor fits a linear model to the data, whereas the support vector regressor fits a nonlinear model.

To evaluate the model performance in the prediction of PHQ-9 scores, we divided the entire dataset into training and test subsets with a ratio of 4:1. Then, we computed the root mean square error (RMSE) of the predicted PHQ-9 scores on the test set and experimented with different selections of feature subsets to decide which combination gave the highest accuracy. The results are shown in Table 1.

The results indicate that by using either teens' inputs or parents' inputs only, we can achieve similar accuracy in PHQ-9 prediction, with the RMSE being 3.38 and 3.47 (the range for PHQ-9 is 0-27), respectively. By using the teens' self-evaluations, as well as SMS, call, steps, and GPS data, we could predict the PHQ-9 score with an RMSE of 3.23. Furthermore, by adding the parents' evaluations, we could reduce the RMSE to 2.65, which is also the lowest error that we could achieve. Conversely, if we use only smartphone sensor and usage data, the RMSE is 2.77.

The major significance of the result is that there appears to be significant predictability of clinical measures from smartphone data. Besides, we could achieve similar PHQ-9 prediction accuracy by using only background sensor data, compared with using both active self-reports and passive sensor data, thereby reducing the efforts of manual inputs. Moreover, parents' inputs provide comparable performance in depression monitoring as teens' inputs. This clearly shows the potential of mobile-based measurements for tracking depressive states and the importance of introducing someone close to the subjects (eg, their parent) as a *human sensor* to provide an additional dimension of data.

Table 1. Root mean square error and variance of predicting Patient Health Questionnaire-9 scores using different subsets of features extracted from smartphone data.

Feature subset	Linear regressor		Support vector regressor	
	RMSE[a]	Variance	RMSE	Variance
All features: both teens' and parents' inputs, steps, GPS, SMS, call, light, and screen	9.36	−10.12	3.88	−0.91
Teens' self-inputs	3.38	−0.45	6.41	−4.21
Parents' evaluations	3.47	0.15	6.30	−4.03
Both teens' and parents' inputs	3.27	−0.36	6.03	−3.61
All sensors: steps, GPS, SMS, call, light, and screen	3.23	−0.32	5.92	−3.44
Steps, GPS, SMS, and call	2.77	0.01	4.77	−1.89
Teens' inputs, steps, GPS, SMS, and call	10.78	−13.03	3.23	−0.33
Parents' inputs, steps, GPS, SMS, and call	3.70	−0.73	3.77	−0.80
Teens' and parents' inputs, steps, GPS, SMS, and call	8.06	−7.24	2.65[b]	0.11[b]

[a] RMSE: root mean square error.

[b] *P*=.017.

Discussion

Principal Findings

The SOLVD-Teen is a first-of-its-kind study that investigated the feasibility of evaluating depressive symptoms of adolescents using smartphone sensor data, daily self-reports, and parental inputs through a customized smartphone app.

The proposed approach worked well for teenagers who are typically heavy smartphone users. Submitting the responses through the app only took less than 15 s per day. Both the teens and their participating parents showed a high adherence rate to submitting daily self-evaluations. All the study participants were comfortable with the use of the technology, and neither the teens nor their parents perceived the app as invasive or burdensome. Besides, the data collection of the study was completely through the smartphone app; hence, no additional sensor or cost was needed. The smartphone app consumes around 5 MB data and 13% battery per day, which is well-acceptable for daily monitoring.

Our study indicated that there were significant correlations between daily self-reported moods, parents' evaluations, and clinical psychometric scores (PHQ-9, HAM-D, and HAM-A). Lower levels of mobility and fewer social interactions were predictive of higher depression symptoms, which was consistent with a decline in mobility and social communications in individuals with depression. However, other daily living contexts such as light intensity and smartphone screen usage were not significantly correlated with depressive symptoms.

Our study expanded on prior studies by suggesting that introducing other people as *human sensors* could further increase the accuracy in depression monitoring. Given the limited sample size, there is no evidence showing that parents' evaluations were biased by their own mental health status. The highest accuracy in predicting PHQ-9 was 90%, which was achieved by combining the teens' and parents' inputs with SMS/call/steps/GPS data. The prediction accuracy could be improved by adding the evaluations from parents apart from self-inputs from the teens. Our study also showed evidence that by using only passive sensor loggings, we could achieve comparable prediction accuracy by using both sensor loggings and self-inputs. Therefore, the SOLVD-Teen app could further reduce user effort by collecting only passive data, while maintaining a comparable depression monitoring effect.

Limitations and Future Work

The study conclusion is preliminary given the relatively small sample size of 13 families. Study recruitment ended as the program from which the patients were recruited shut down for logistic reasons as the AIM program closed. In addition, 8 out of the 13 families completed the entire 8-week trial: the program necessitated biweekly attendance, which created a burden (time spent at the program and transportation costs and effort), but the treatment team noted that families tended to drop out once their child did better, and intensive treatment was not felt to be as crucial. We plan to extend the study with the reopening of the AIM program in a different location.

In college-aged students, increased ruminations were found to relate to increasing depressive symptoms [26]. Similarly, nonsuicidal self-injury correlates with self-criticism and feeling criticized by others and usually links to a negative affect of brief durations [27]. Such brief moments of ruminations and self-blame are the epitome of what smartphone apps can help us capture and leverage into treatment opportunities. Thus, the aim of mobile health interventions is to move the treatment of adolescents with mood disorders from reactive to proactive and personalized, thus paving the way to truly individualized treatments [28].

In summary, the SOLVD-Teen study verified the feasibility of using smartphone user inputs and background sensor loggings to monitor adolescent patients with MDD. Its key novelty lies in the recruitment of adolescent depression patients and the introduction of parental evaluations as an additional source of inputs. The study was limited by the relatively small sample size and the constraint of using only Android phones because of the lack of permission to access certain sensors on the iOS platform.

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Authors' Contributions

JC and AS developed the SOLVD apps and did the data analysis. AT, SB, AS, and NM participated in the subject recruitment and data collection. All authors participated in the clinical trial design and manuscript preparation.

Conflicts of Interest

None declared.

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Abbreviations

AIM: Adolescents in Motion
EMA: ecological momentary assessment
HAM-A: Hamilton Anxiety Rating Scale
HAM-D: Hamilton Rating Scale for Depression
IRB: institutional review board
MDD: major depressive disorder
MINI: Mini International Neuropsychiatric Interview
PHQ-9: Patient Health Questionnaire-9
RMSE: root mean square error
SOLVD: Smartphone- and OnLine usage–based eValuation for Depression
WHO: World Health Organization

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Original Paper

The Role of Campus Data in Representing Depression Among College Students: Exploratory Research

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Abstract

Background: Depression is a predominant feature of many psychological problems leading to extreme behaviors and, in some cases, suicide. Campus information systems keep detailed and reliable student behavioral data; however, whether these data can reflect depression and we know the differences in behavior between depressive and nondepressive students are still research problems.

Objective: The purpose of this paper is to investigate the behavioral patterns of depressed students by using multisource campus data and exploring the link between behavioral preferences and depressive symptoms. The campus data described in this paper include basic personal information, academic performance, poverty subsidy, consumption habit, daily routine, library behavior, and meal habit, totaling 121 features.

Methods: To identify potentially depressive students, we developed an online questionnaire system based on a standard psychometric instrument, the Zung Self-Rating Depression Scale (SDS). To explore the differences in behavior of depressive and nondepressive students, the Mann-Whitney U test was applied. In order to investigate the behavioral features of different depressive symptoms, factor analysis was used to divide the questionnaire items into different symptom groups and then correlation analysis was employed to study the extrinsic characteristics of each depressive symptom.

Results: The correlation between these factors and the features were computed. The results indicated that there were 25 features correlated with either 4 factors or SDS score. The statistical results indicated that depressive students were more likely to fail exams, have poor meal habits, have increased night activities and decreased morning activities, and engage less in social activities (eg, avoiding meal times with friends). Correlation analysis showed that the somatic factor 2 (F4) was negatively correlated with the number of library visits (r=–.179, P<.001), and, compared with other factors, had the greatest impact on students' daily schedule, eating and social habits. The biggest influencing factor to poor academic performance was cognitive factor F1, and its score was found to be significantly positively correlated with fail rate (r=.185, P=.02).

Conclusions: The results presented in this study indicate that campus data can reflect depression and its symptoms. By collecting a large amount of questionnaire data and combining machine learning algorithms, it is possible to realize an identification method of depression and depressive symptoms based on campus data.

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KEYWORDS

depression; mental health; behavior analysis

Introduction

Depression is a serious mental health issue that affects a significant segment of the population and has become a leading cause of disability and suicide. It is estimated that nearly 300 million people suffer from depression [1]. The best time to address this health problem is before symptoms disrupt patients' daily life—for example, early warning of mood changes and anxiety can dramatically reduce chronic psychological distress and loss of function [2-4]. Analyses of behavior, sentiments, and other outward signs of depression are of great importance to the diagnosis and treatment of patients.

As students suffer from pressure stemming from financial status, academic demand, interpersonal relationship [5], and career [6], college campuses are among the environments hardest hit by depression. Depression leads to poor academic performance [7,8], drinking problems [9], suicidal thoughts [10,11], frequent illness [12], and dropout [13] and is prevalent in many countries [14-19]. According to a survey reported by the US Centers for Disease Control and Prevention in 2017, 31.5% of US students nationwide reported feeling so sad and hopeless almost every day that they stopped doing some usual activities [20]. Similar phenomena were discovered by the American College Health Association after they studied 80,121 students from 106 schools in 2009 [21]: 43% of the respondents reported that at least once within the previous school year they "felt so depressed that it was difficult to function," and more than 62% "felt hopeless." Moreover, the proportion of depressive students has been reported to have increased rapidly during recent years [6] by many universities and associations.

The situation in Chinese colleges is far from optimistic as well. In a review of 39 studies including 32,694 university students, Lei et al [22] indicated that the overall prevalence of depression among Chinese students was 23.8%, highlighting the urgent need to tackle the issue.

At present, mental health services provided on college campuses are inadequate. Students taking the initiative to ask for help and report their symptoms are the first indication for the deployment of mental health counseling services; however, the proportion of students who actively reported psychological problems was only 18% [23]. A promising approach is to identify useful clinical behavior indicators and use them to estimate the occurrence of depression.

Behavioral models of depression suggest that decreased response-contingent positive reinforcement for previously rewarded behaviors is the central fact for bringing about depression [24]. Decreased positive reinforcement may be caused by changes in the quantitative or qualitative aspects (eg, social, intellectual; function: stimulation seeking, achievement) of the reinforcing events, availability of reinforcement in the environment (eg, social isolation, poverty), inadequate instrumental behaviors (eg, social skill, academic ability), and/or the result of an increased frequency of punishment [25]. The theory implies the possibility that some external characteristics may explain or lead to depression. In the case of a university campus, data that can reflect these characteristics include basic personal information, academic performance, poverty subsidy, consumption, daily routine, library use, meal habit, sport, club activity, etc.

Depression is a common disorder that impacts an individual's ability to perform life activities, including those required by academic life. The significant negative relationship between depression and academic performance was identified by many researchers [26,27], showing that students suffering from moderate levels of depression demonstrated lower performance compared with those with normal and mild levels of depression [26]. Reading preference as an important factor contributing to academic performance was also found to correlate with depression [28].

Food and eating habits have an impact on the development of depression, and depression can, in turn, affect the patient's eating routine [29]. A study on dietary habits and food intake in adults aged 50 years and older revealed that people in the depressed group had a poor appetite, almost never dined out, and ate alone [29]. Vice versa, altered eating behaviors showed elevated levels of impulsivity and depression [30].

Social relationships play a key role in depression. One typical feature of the disorder is social isolation and social withdrawal [31]. Another core characteristic is anhedonia—loss of interest or pleasure in previously enjoyable activities [32]. Depressed patients tend to opt out of social situations, either formally (eg, exiting an art group) or informally (eg, being unwilling to see friends). Moreover, for most depressed patients, their social connections have already been significantly reduced prior to the development of depression symptoms. Therefore, the reduction of social connections is a key feature of depression, and this is more prevalent than in other physical and mental illnesses [33]. Cacioppo et al [34] found that even after controlling for key candidate variables such as demographics, personality, physical health, stress, and many factors related to social relationships, perceived social isolation is a good longitudinal predictor of depressive symptoms.

Mood disorder can be considered a biorhythm disorder [35]. The symptomatology of depression implies that a biological clock disorder may result in the occurrence of depression [35]. This is also why depression is associated with sleep disorders. For example, the time between falling asleep and the first rapid eye movement sleep in a depressed patient is much shorter than that of a nondepressive person [36]. In addition to being manifested in sleep disorders, biorhythm disorders can also cause disorders in other physiological mechanisms. For people with depression, the severity of mood and other symptoms also fluctuate during the day [37]. They feel worse in the morning, and the situation is slightly better during the day. Other biological rhythms, such as body temperature and cortisol level, also become irregular [36]. On the other hand, depressed persons have their own activity preferences. By investigating a sample of 400 undergraduate students, Sheslow et al [38] found that nondepressive students tended to eat with others and engage with others more often than depressive students, and they implied that depression in the university population is correlated with small changes in a large number of daily activities. However, there is currently no literature on the relationship between depression and its symptoms and daily routine preferences of college students.

It is worth noting that depression consists of a variety of symptoms. In most studies that use the Zung Self-Rating Depression Scale (SDS) for measuring levels of depression, the total score was used as an indicator of the severity of depression; however, overreliance on the total score of the SDS is undesirable [39] and may not be able to identify different types of depression because various profiles of heterogeneous symptoms are included in a single dimension of severity. For example, the total score cannot distinguish between those who are mainly suffering from physical symptoms and those who are mainly affected by affective symptoms [40]. It is necessary, therefore, to study the related influencing elements of various symptoms of depression.

As summarized above, there are two main shortcomings of current body of literature with regard to the subject of college student depression. First, there is a lack of research on the relation between college students' depression and their behavior, essential for a better understanding of the behavior pattern of the affected. Second, previous studies were mainly based on questionnaire surveys, which may bring about the pervasive problem of social desirability bias [41].

Methods

Questionnaire

The SDS [42] was used as the primary tool to determine the depression levels of college students. It is a 20-item Likert-type instrument (4-point scale) to measure depressive affect and related symptomatology during a week by seeking responses to questions such as "I feel downhearted and blue," "Morning is when I feel the best," and "I have crying spells or feel like crying." Participants were asked to choose one of the following responses to each of the questions: 1=rarely or none of the time (<1 day), 2=some or a little of the time (1-2 days), 3=occasionally or a moderate amount of the time (3-4 days), 4=most or all of the time (5-7 days).

SDS is one of the most common screening tests used by clinicians and psychiatrists. Participants' raw scores ranged from 20 to 80. The higher the scores, the higher the occurrence of symptomatology. The standard point of the SDS is obtained by multiplying the raw score by 1.25. According to the Chinese norm for the general public, scores of 53 to 62 are classified as mild depression, 63 to 72 moderate depression, and 72 to 100 severe depression. SDS has an adequate item homogeneity; Knight et al [43] reported an alpha coefficient of .79 in a large community sample, and Gabreys and Peters [44] reported an alpha value of .88 in a sample of depressed patients.

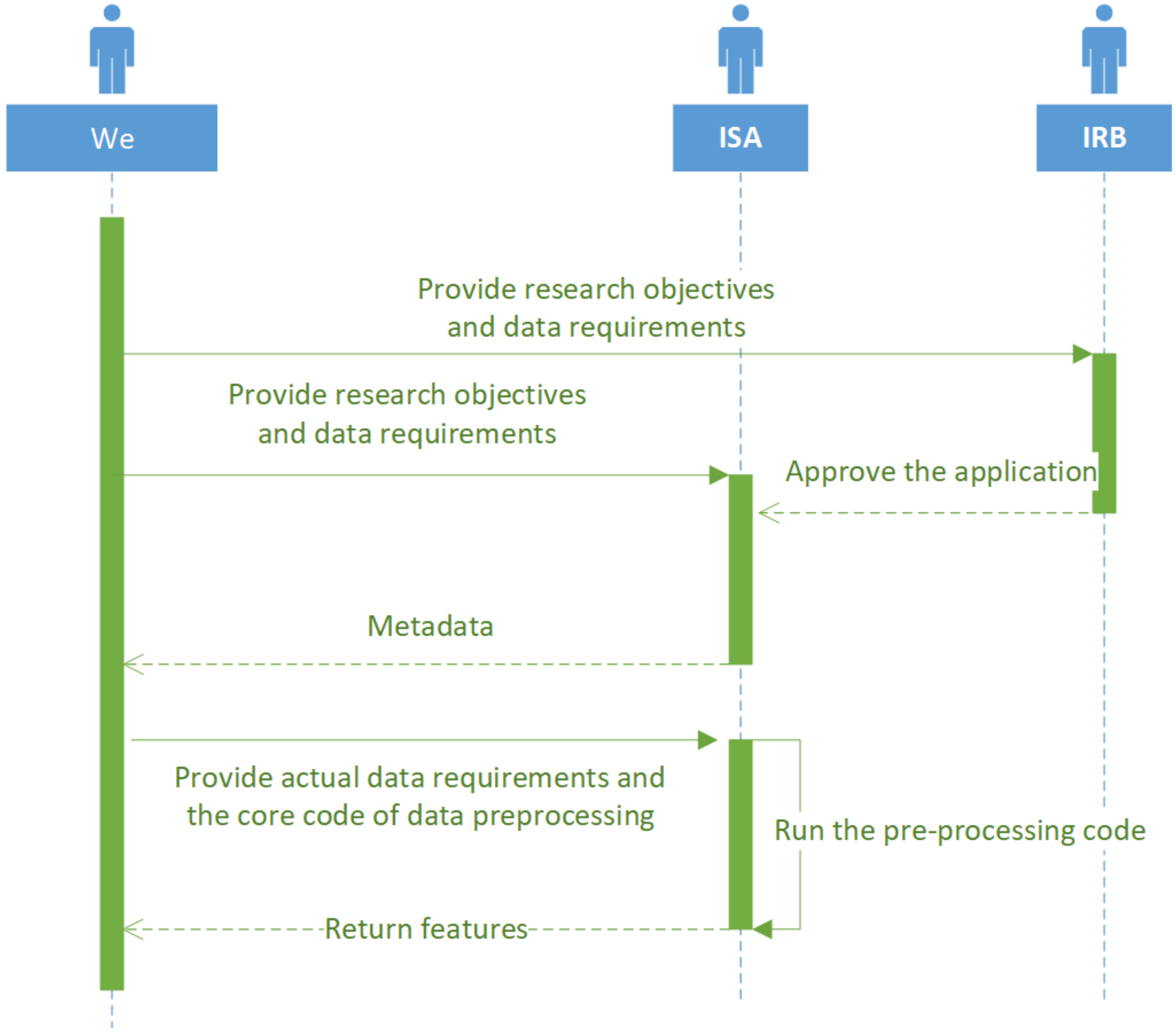
In this paper, we developed an online questionnaire system and only allowed students connected to the campus network to participate in it. In order to control the accuracy of the questionnaire results, we recorded the duration of answering and removed students who completed the form in less than 5% of the overall time distribution and used the Beck Depression Inventory (BDI) [45] as a supplementary questionnaire to detect biased answers. As conclusions drawn by SDS and BDI are strongly related to each other theoretically, we deleted very contradictory items (eg, when the SDS showed that one student suffered from moderate to severe depression while the BDI indicated no depression). We also excluded participants who never had breakfast at the college canteens because they may be off-campus students.

Privacy Protection

We fully considered the privacy of students. First, we signed a data confidentiality agreement with the information management department and passed the ethical review of the University Department of Medical and Life Sciences (No 2018YXY24). Second, we indicated the purpose of the experiment, the type, and the time period of the use of the data on the first page of the questionnaire to let the participants know about this study.

With respect to the feature extraction, we designed a process to meet the regulations. We first gave the objectives and data requirements to the institutional review board and the information system administrator (ISA). After that, we got the metadata, such as field names with their meanings, data types, etc, of related tables from ISA. Subsequently, we provided detailed data requirements and the core code of data preprocessing. Furthermore, ISA wrote other auxiliary codes (eg, database accessing codes) and ran the whole preprocessing code on their own computers, and we finally got the features which did not contain any sensitive information such as students' names and home addresses. In the whole process, we did not access any school information systems and therefore could not obtain any other private data. The process is illustrated in Figure 1.

Figure 1. Data acquisition process.



Units of Observation

The research conducted by Kessler et al [46,47] showed that depression episodes characterized as mild to severe have an average duration of 13.8 to 16.6 weeks, and very severe episodes have a mean duration of 23.1 weeks. The overall mean duration is 16 weeks. As one semester (18 weeks) is a complete cycle of student life on campus, we used data generated in the first semester of 2017 academic year (from September 11, 2017, to January 10, 2018) as the research subject for the study. The questionnaire data were collected from December 29, 2017, to January 28, 2018, and social relationship data were generated from November 20, 2017, to January 10, 2018.

Definition of Symptoms

In order to determine the symptom groups contained in the SDS, Zung divided the SDS items into three groups based on the overt content of symptoms: pervasive affect (depressive affect and crying spells), physical equivalents (diurnal variation, sleep disturbance, decreased appetite, decreased libido, weight loss, constipation, tachycardia, and fatigue), and psychological equivalents (confusion, psychomotor retardation and agitation, hopelessness, irritability, indecisiveness, personal devaluation, emptiness, suicidal ideation, and dissatisfaction) [42]. Other literature [40,48,49] adopted factor analysis to identify common clusters across different types of people, but this is difficult because the profiles of depressive symptoms vary in different populations [48].

Although some literature proposed factor structures of college students, their conclusions may not be suitable for Chinese students because of the differences in the populations. Therefore, we redivided the SDS questionnaire into different depression symptom groups using factor analysis. The accumulated score of items that belonged to each symptom group was used to represent the severity of the symptom.

Introduction to the Features

Raw Features

Most students in Chinese universities are now required to have their own student cards as identification and digital wallets to access facilities, make payments on campus, etc. Daily routines, eating behavior, and consumption behavior features were extracted by analyzing the student card events logged by the door control and consumption systems. Data generated on festival and nonfestival days were analyzed separately because students might behave differently during festivals (eg, students tend to get up late and come back late in holidays, which results in an irregular schedule). Features are summarized into 7 categories based on their characteristics and are listed in Textbox 1.

With respect to scholarship, the total amount of the award since enrolled, the amount of award obtained in the last academic year, and the number of scholarships won were obtained. Students' exam scores were divided into 5 levels according to college tradition (excellent, good, average, pass, and fail).

Textbox 1. Feature categories, feature details, and numbers of features.

Basic personal information:

- Gender (1)
- Grade (1)

Academic performance:

- Scholarship (3)
- Exam score (15)

Poverty subsidy:

- Number of applications of poverty subsidies (1)
- Applied for poverty assistance this year (1)

Consumption:

- Monthly consumption behavior (6)
- Weekly consumption behavior (4)
- Water intake at the dormitory (1)

Daily routine:

- Number of times returning to and leaving the dormitory (1)
- Number of times returning to and leaving the dormitory every hour during nonfestivals (days that are not festival days; 37)
- Number of times returning to and leaving the dormitory every hour during festivals (statutory holidays in China except for Saturday and Sunday; 32)

Library behavior:

- Number of times visiting the library (1)
- Total number of books borrowed (1)
- Number of books borrowed in the semester (1)

Meal habit:

- Standard deviation of time of breakfast during nonfestivals (1)
- Average time for breakfast during nonfestivals (1)
- Number of breakfasts during nonfestivals (1)
- Number of breakfasts during festivals (1)
- Standard deviation of time of lunch during nonfestivals (1)
- Average time for lunch during nonfestivals (1)
- Number of lunches during nonfestivals (1)
- Number of lunches during festivals (1)
- Standard deviation of time of dinner during nonfestivals (1)
- Average time for dinner during nonfestivals (1)
- Number of dinners during nonfestivals (1)
- Number of dinners during festivals (1)

Student Card-Based Social Features

An assumption was proposed that depressed students tend to avoid meal times with their companions; if this assumption is valid, depressed students and their friends will be significantly less likely to use their student cards at the same time in the cafeteria than that of nondepressed students. Social behavior features can be defined as follows: in the equations seen in Figures 2 and 3, 1(.) is indicator function (1[true statement]=1 and 1[false statement]=0), *i* stands for the target student whose social features need to be calculated, and *j* stands for another student. M and N are swiping times of students *i* and *j*, respectively, and S_{im} represents for the m_{th} time when the student uses his/her student card at the campus canteens. *T* represents the time span, which was 250 seconds in this work; R_{ij} is the social frequency between student *i* and student *j*, so the larger R_{ij} is, the more times person *i* and person *j* shared meal times and the closer the relationship they have. *sorted(.)* is a sorting function that sorts the elements of the matrix from largest to smallest. We selected the maximum 5 values of R_i as student *i*'s social features, which are named as TOP_1, TOP_2, TOP_3, TOP_4, TOP_5 in the following text. The effectiveness of this feature is introduced in the following section.

Figure 2. Social interaction frequency matrix.

$$R_{ij} = \sum_{m=1}^{M} \sum_{n=1}^{N} 1\left(\left(S_{im} - S_{jn}\right) < T\right), i \neq j$$

Figure 3. Computational method for social behavior features.

$$TOP_k^i = sorted(R_i)_k$$

Results

Mental Health Questionnaire Results

Out of 502 undergraduate students who participated in the research, 466 students were selected as research subjects and their detailed information is shown in Table 1.

Of the participants, 69.5% (324/466) were boys and 30.5% (142/466) were girls. Ages ranged from 17 to 23 years. Grades ranged from one to six and the majority were first-year students (214/466, 45.9%). The reason there were two six-grade students in the sample is that some students repeated a grade because of various reasons (eg, receiving medical treatment).

The mean depression score of male students was 46.38, while the females' was 49.14. The ratio of students suffering from depression was 25.32%, with mild depression (16.31%) taking the majority, and a small proportion of students were found suffering from moderate (6.44%) to severe (2.58%) depression. We used the chi-square test to determine the gender difference in depression rate, and the results are shown in Table 2.

The Mann-Whitney *U* test is a widely used nonparametric test to decide whether two groups of samples are derived from the same population. Since most of the features in this study deviated from the normal distribution, the nonparametric Mann-Whitney *U* test was used to determine whether there were differences between the two groups with respect to the behavior on campus.

The test indicated there were 25 features significantly different between depressive and nondepressive groups, and the results are listed in Table 3.

The result showed $\chi 2=10.0$ (*P*=.02), which indicated different genders had different rates of depression levels. Post hoc testing demonstrated that female students had a higher depression rate than male students (odds ratio [OR] 0.54, 95% CI 0.349-0.835); more specifically, female students had a higher risk of mild depression (OR 0.473, 95% CI 0.286-0.783), while there was no statistical difference in moderate and severe depression.

Table 1. Basic information of the participants.

Characteristics	Value n (%)
Gender	
Female	142 (30.5)
Male	324 (69.5)
Age in years	
17	16 (3.4)
18	170 (36.5)
19	96 (20.6)
20	72 (15.5)
21	74 (15.9)
22	30 (6.4)
23	8 (1.7)
Grade	
First year	214 (45.9)
Sophomore	83 (17.8)
Junior	75 (16.1)
Senior	82 (17.6)
Five grade	10 (2.1)
Six grade	2 (0.4)

Table 2. Mental health questionnaire results.

Gender	Nondepression		Depression					
			Mild		Moderate		Severe	
	n (%)	ASR[a]	n (%)	ASR	n (%)	ASR	n (%)	ASR
Female	94 (66.20)	–2.8	34 (23.94)	3.0	9 (6.34)	–0.1	5 (3.52)	0.9
Male	254 (78.40)	2.8	42 (13.00)	–3.0	21 (6.48)	0.1	7 (2.16)	–0.9

[a] ASR: adjusted standardized residual.

Table 3. Mann-Whitney U test results.

Variables	Mann-Whitney *U*	Z-score	Asymptotic significance (2-tailed)	Mean value of nondepressive group	Mean value of depressive group
Number of breakfasts	17692.00	–2.25	0.025	52.77	45.81
SD of time of breakfast	16089.00	–2.91	0.004	0.70	0.77
Number of lunches	17071.50	–2.74	0.006	71.93	64.76
Number of lunches during festival[a]	16491.00	–3.22	0.001	4.30	3.23
Lunch Time	16806.00	–2.95	0.003	11.75	11.80
Dinner Time	17445.00	–2.44	0.015	17.47	17.60
Number of dinners	17661.50	–2.27	0.023	65.54	59.25
TOP_1	17479.00	–2.42	0.016	47.59	42.26
TOP_2	17295.00	–2.56	0.010	44.48	39.36
TOP_3	17191.50	–2.64	0.008	42.97	38.13
TOP_4	17234.50	–2.61	0.009	41.97	37.27
TOP_5	17304.00	–2.55	0.011	41.97	37.27
8-9 R[b]	17690.50	–2.31	0.046	3.26	1.94
9-10 R	16063.50	–3.56	0.050	4.80	3.11
10-11 R	17923.00	–2.09	<0.001	3.31	2.36
10-11 O[c]	17450.00	–2.46	<0.001	3.04	3.60
11-12 R	18334.50	–1.99	<0.001	0.80	0.52
13-14 O	17771.00	–2.20	0.008	4.08	4.85
14-15 R festival	18174.50	–2.36	0.012	0.35	0.52
19-20 R festival	17864.00	–2.34	0.014	0.69	1.03
20-21 R	18010.00	–2.00	0.018	7.90	8.89
21-22 R	17352.50	–2.52	0.019	8.28	9.75
22-23 R	14948.50	–4.43	0.021	6.32	9.77
23-24 R	15342.00	–4.25	0.028	2.22	4.36
23-24 O	17501.50	–2.64	0.037	1.72	2.47

[a] Features unlabeled with festival refer to nonfestival days.

[b] R: return to the dormitory.

[c] O: leave the dormitory.

Behavioral Differences Between the Two Groups of Students

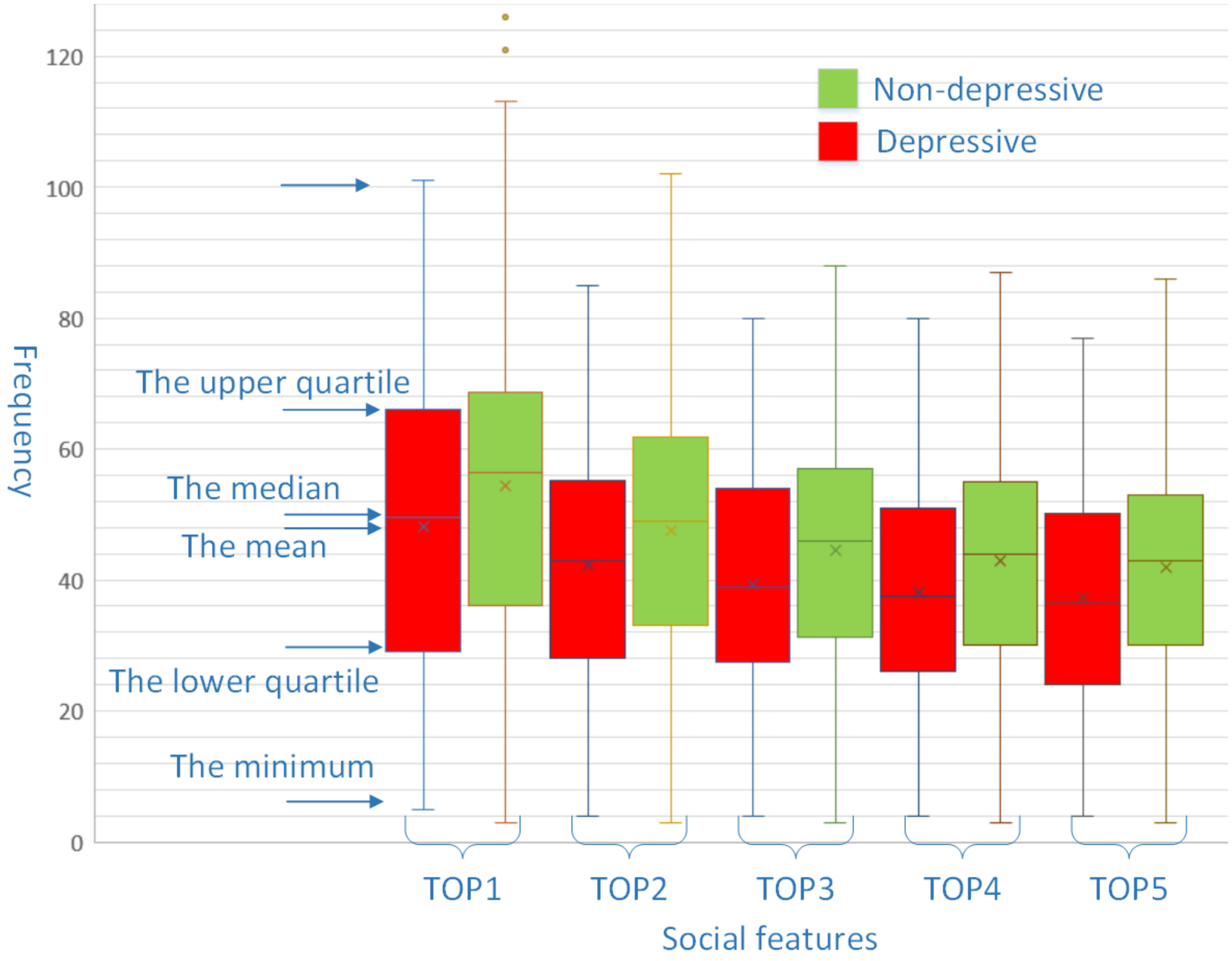
Eating behavior was found to be different between the two groups of students: depressive students (*u*=45.81) skipped breakfasts significantly more often than nondepressive (*u*=52.77) students (*z*=–2.25, *P*=.03). The same was observed for lunch and dinner. In addition, the breakfast time of depressive students was later than that of nondepressive students (*z*=–2.91, *P*=.004), and lunch and dinner time were also later.

With regard to daily schedule preferences, the number of depressive students entering the dorm in the morning was significantly less than that of nondepressed students. In addition, the night activity of depressed students (ie, the average number entering or leaving the dorm between 8 pm and midnight was significantly busier than that of nondepressive students.

Regarding social interaction, all 5 social features of depressive students were significantly lower than their counterparts. Figure 4 illustrates the distribution of social behavior features of the two groups. The box plot indicates that the lower quartile, average, median, upper quartile and maximum of the depressive group are all lower than nondepressed students. It is, in turn, revealed that the student card–based social relationship features proposed in this paper can reflect students' social characteristics.

The number of poverty subsidy applications of depressive and nondepressive students was statistically different (χ2=4.2, *P*=.04), with the application rate of poverty subsidy in the nondepressed group 4.90% and depressed group 10.17%, suggesting that there is a higher rate of depression among economically disadvantaged students.

Figure 4. The distribution of social frequency of depressive and non-depressive students.



Factor and Correlation Analyses

Correlation analysis showed that there was a high correlation between the vast majority of items on the SDS, which means it is possible to use a few factors to summarize most of the information contained in the original 20 entries. Principal component factoring with promax (oblique) rotation was adopted to evaluate the factor structure of the SDS in this study. The Bartlett test of sphericity was significant ($\chi 2$=2505.6, *P*<.001), and the Kaiser-Meyer-Olkin measure of sampling adequacy was 0.92, indicating the rationality of principal component factoring.

The eigenvalues of the first 4 principal components were greater than 1, and the variations were 30.15%, 8.01%, 5.72%, and 5.34%, respectively. The cumulative variance was 49.23%. The rotated factor pattern matrix is given in Table 4.

The first factor (F1) was composed of 10 items: decreased libido, personal devaluation, psychomotor retardation, dissatisfaction, decreased appetite, confusion, hopelessness, emptiness, indecisiveness, suicidal ideation. The second factor (F2) was composed of 6 items: crying spells, irritability, fatigue, sleep disturbance, psychomotor agitation, and depressed affect. Factor III (F3) consisted of 3 items: constipation, weight loss, tachycardia. Factor IV (F4) consisted of only one item: worse in the morning. Unlike factor analysis results of some literature [40,48,49], diurnal variation (worse in the morning) was the only item that has large loading in F4. We summed up the scores of all items belonging to each factor or symptom group as the score or severity of the symptom.

Table 4. Promax rotated factor pattern matrix (N=466).

Factor and item	F1	F2	F3	F4
Factor I: cognitive (F1)				
Decreased libido (6)	0.731	0.263	–0.032	0.040
Personal devaluation (17)	0.681	0.029	0.044	0.312
Psychomotor retardation (12)	0.678	–0.058	0.112	–0.171
Dissatisfaction (20)	0.651	–0.049	–0.089	–0.021
Decreased appetite (5)	0.624	0.088	–0.208	–0.424
Confusion (11)	0.615	–0.132	–0.067	–0.189
Hopelessness (14)	0.609	–0.105	0.030	0.221
Emptiness (18)	0.589	–0.156	0.132	0.312
Indecisiveness (16)	0.583	–0.054	0.090	0.069
Suicidal ideation (19)	–0.503	0.056	0.087	0.033
Factor II: manifest depressed mood (F2)				
Crying spells (3)	0.125	0.727	–0.057	–0.043
Irritability (15)	0.015	0.648	0.063	0.174
Fatigue (10)	0.004	0.640	0.161	–0.057
Sleep disturbance	–0.049	0.415	0.211	–0.006
Psychomotor agitation (13)	–0.054	0.754	–0.074	0.056
Depressed affect (1)	–0.165	0.674	–0.112	–0.052
Factor III: somatic 1 (F3)				
Constipation (8)	–0.022	–0.125	0.820	–0.359
Weight loss (7)	–0.029	–0.016	0.549	0.175
Tachycardia (9)	0.139	0.379	0.587	–0.054
Factor IV: somatic 2 (F4)				
Worse in the morning (2)	0.074	0.045	–0.135	0.730

Daily Routine

Table 5 shows the Spearman correlation between daily routine features and the four factors and the total SDS score.

Among the 4 factors, F4 can be reflected in daily routine most, and the reason for the correlation may be that depression disrupted circadian rhythms [50]. Students with higher levels of depressed mood (F2) and somatic (F3, F4) depressed symptoms partially result in increased night activity, while a decrease in morning activity is partially caused by cognitive (F1), depressive mood (F2), and somatic (F4) symptoms (see Multimedia Appendix 1 for detailed information).

Table 5. Spearman correlation between the factors and daily routine.

Scores	6-7 R[a]	7-8 R	7-8 O[b]	8-9 R	8-9 O	9-10 O	23-0 R	23-0 O	0-1 O
F1	.03	–.01	–.109[c]	–.06	–.07	–.125[d]	.05	.07	–.01
F2	.08	.03	–.07	–.07	–.08	–.162[d]	.129[d]	.188[d]	.128[d]
F3	.096[c]	.00	–.01	–.04	–.05	–.05	–.04	.092[c]	.102[c]
F4	–.172[d]	–.179[d]	–.119[d]	–.201[d]	–.165[d]	–.162[c]	.128[d]	.098[c]	.09
SDS[e]	.06	–.01	–.111[c]	–.096[c]	–.105[c]	–.170[d]	.07	.134[d]	.07

[a] R: return to the dormitory.

[b] O: leave the dormitory.

[c] Correlation is significant at the .05 level (2-tailed).

[d] Correlation is significant at the .01 level (2-tailed).

[e] SDS: total Zung Self-Rating Depression Scale score.

Meal Habit

Depression symptoms can result in changes in appetite [29]. Intuitively, these changes may be reflected in the dining data. To test this hypothesis, we performed the Spearman rank correlation analysis between meal habits and depression symptoms, and the test results are shown in Table 6.

As can be seen from the table, F4 correlates with most meal habit features with high confidence. Feeling worse in the morning can lead to poor meal habits, such as a high rate of skipping meals and irregular eating.

Table 6. Spearman correlation between the factors and meal habits.

Scores	SD breakfast time	Mean breakfast time	Number of breakfasts	Number of lunches	Number of dinners
F1	.066	.007	–.053	–.064	–.050
F2	.166[b]	.035	–.083	–.078	–.037
F3	.115[a]	.054	–.014	–.036	–.021
F4	.153[b]	.161[b]	–.275[b]	–.151[b]	–.135[b]
SDS[c]	.129[b]	.038	–.100[a]	–.086	–.064

[a] Correlation is significant at the .05 level (2-tailed).

[b] Correlation is significant at the .01 level (2-tailed).

[c] SDS: total Zung Self-Rating Depression Scale score.

Academic Performance

As most students should accomplish the majority of courses in the first two years of college life, first-year students are empirically found to be more serious about their study compared with higher year students, therefore we only use first-year student data (214 students) to investigate associations between academic performance and the severity of depression. The result of Spearman correlation is reported in Table 7.

Compared with other factors, F1 has the greatest impact on performance, especially for the two extremes, fail and excellent. When the F1 score is high, it is easier to fail exams or to get general grades. However, the total SDS score was only found to significantly correlate with the fail course rate and the number of failed courses. The table suggests that depression makes it easier for students to have bad academic performance, even if the total score does not reach the threshold of depression.

Table 7. Spearman correlation between depression and academic performance.

Scores	Excellent rate	Fail rate	Number of excellent	Number of good	Number of fail
F1	–.158[a]	.185[b]	–.137[a]	.157[a]	.186[b]
F2	.061	.150[a]	–.043	.071	.155[a]
F3	.108	.090	.117	–.061	.097
F4	–.050	.132	–.039	.018	.140[a]
SDS[c]	–.111	.195[b]	–.087	.116	.201[b]

[a] Correlation is significant at the .05 level (2-tailed).

[b] Correlation is significant at the .01 level (2-tailed).

[c] SDS: total Zung Self-Rating Depression Scale score.

Social Behavior

The distribution of social behavior features is normally distributed, so we tested the Pearson correlation between features and 4 facts and SDS score. The result is shown in Table 8.

The table indicates that F4 had the largest effect on social activity, students who felt bad in the morning were more reluctant to share meal times with their friends, while the total SDS score only has a weak relationship with social activity.

The relationship between the frequency of library access and depression was also explored, F4 was found to be negatively correlated with the number of library visits (r=–.179, P<.001). No difference was found in the acquisition of scholarships.

Table 8. Pearson correlation between social features and depression.

Scores	TOP_1	TOP_2	TOP_3	TOP_4	TOP_5
F1	–.053	–.064	–.064	–.055	–.054
F2	–.094[a]	–.096[a]	–.093[a]	–.084	–.083
F3	–.059	–.056	–.050	–.037	–.042
F4	–.166[b]	–.156[b]	–.164[b]	–.171[b]	–.166[g]
SDS[c]	–.096[a]	–.102[a]	–.101[a]	–.091[a]	–.090

[a] Correlation is significant at the .05 level (2-tailed).

[b] Correlation is significant at the .01 level (2-tailed).

[c] SDS: total Zung Self-Rating Depression Scale score.

Discussion

Principal Findings

Being a serious mental disorder, depression affects the life of patients in both mental and physical aspects. There is a critical need to identify behavior characteristics for better identifying and even helping the treatment of depression; however, to the best of our knowledge, research on depression among college students with campus data has not been conducted.

The meal habits of depressive students in this research were different from that of nondepressive students; this finding is congruent with the finding of Lee et al [29] that implied depression may affect the dietary habits. Our experiments indicated students with depression tended to have bad eating habits. Factor analyses indicated feeling bad in the morning was a contributor to the phenomena; furthermore, irregular breakfast time was caused by complicated symptoms except for cognitive factor.

Depressed students were found to have fewer morning activities and more night activities; furthermore, factor analyses indicated that decreased morning activity was affected by factor 4 (feeling bad in the morning), while increased evening activity was partially caused by factor 2 (depressed mood) compared with other symptoms.

Our findings on daily routine and meal habits are consistent with the well-established literature that suggests biologic rhythm is associated with depression [35-38,51-53]. Disruptions in behavioral patterns caused by depression during waking hours includes not only the volume of activity but also the patterns of behavior [53,54]. These pattern changes may be a result of the genetic and hormonal factors [36] implicated in depression-related circadian rhythm changes [53,54].

With respect to social interaction pattern, the Mann-Whitney *U* test and correlation analyses demonstrated that depression impaired social activity, and this conclusion is congruent with previous studies [38,55]. Furthermore, our study demonstrated that social activity extracted in this research was mainly affected by diurnal variation (F4), while cognitive symptoms (F1) and somatic symptoms (F3) had no connection with decreased social activity.

Many studies have investigated the negative impact of depression on academic performance [5,26,56], and our study goes further on this topic. Factor analyses demonstrated that there was a negative correlation between depression and course fail rate among first-year students. Moreover, by investigating the relationship between academic performance and each factor, we found that the cognitive factor (F1) was the most relevant factor for poor academic performance. Students with high cognitive symptom were more likely to fail exams and less likely to achieve excellent academic performance [57].

Finally, through the chi-square test we found that the proportion of poverty subsidy application was not the same between depressive and nondepressive students. The application proportion of the depressive group was significantly higher than the nondepressive group, which indicates that family economic status is one of the impact factors in depression. This conclusion fits into previous studies, which demonstrated poor socioeconomic background is associated with depressive symptoms within each country [5,56].

Limitations

Although our research reveals that some behavioral characteristics of depressive students can be captured by campus data, the results are preliminary and a number of limitations must be mentioned.

First, the work has not covered all aspects of students' life on campus (eg, data related to location, physical exercise, after school clubs, course selection) due to the limitation of school information infrastructure. With respect to meal habits, because there are other places for students to eat except for the campus canteen, it is impossible to accurately obtain all the dining information. Thus, the term meal habits described in the paper only represents the meal habits in the campus canteen.

Second, although some patterns about depressive students' daily routines were found, specific reasons need to be further clarified through a questionnaire survey.

Third, this research adopted the method of self-reported questionnaire survey to determine whether participants were depressed, which may bring about the pervasive problem of response bias [58].

Finally, students with different levels of depression may behave differently. Because of the low number of students who suffered from moderate to severe depression, behavioral differences among mild, moderate, and severe depression were not explored.

Implications and Future Work

This paper proves that campus data can reflect student depression status and indicates that depression may be predicted by using machine learning techniques. Because timely rescue of potentially depressed students can improve their academic performance and reduce their own pain and suicide risk, depression prediction has good practical effects.

Privacy presents a major problem. To precisely predict students' mental health problems, too much privacy data such as online behavior, daily routine, family background, and consumption level may be involved. Thus, it is recommended that data providers convert or add noise to the original data to protect privacy. For example, provide researchers with differential privacy [59] processed data.

In addition, data-driven mental health prediction methods can lead to some negative effects, and the feedback loop is a topic worthy of consideration because it creates some problems.

The principle of educational equity may be violated. Managers may prefer not to grant scholarships to depressed students because they may perform poorly, and this would reduce their chances of participating in academic, community, and competition activities. This could be addressed by developing a mental health prediction system that can only be used by those whose jobs are related to mental health care. When the system finds a depressed student, a psychological counselor will contact the student directly to decide whether it is appropriate to recommend that they ask for psychological counseling services according to the actual situation. Because of direct communication between the counselor and depressed student, no other students or teachers would know the specific situation, therefore eliminating the problem of educational inequality that may be caused by depression.

Although data management rights belong to the information technology department, it does not mean that the department has full rights to the data. Some operations on the data are forbidden to perform unless permitted by students. Some students may be concerned about mental health issues or personal privacy being exposed, which may result in a refusal of authorization. Therefore, some depressive students will not be detected by the system. To address this, we will popularize mental health knowledge on campus to eliminate student stigma about mental illness and explain to students how the system works to eliminate their concerns about privacy.

Conclusions

The campus information systems run all the time and record all aspects of students' living on campus. Compared with the traditional questionnaire survey method, these data can reflect behavior and psychological activities more objectively and realistically, and there is almost no cost to obtain this data compared with other types of data (eg, mobile phone use) [54]. This paper proves that depressive students have different behavioral characteristics than nondepressive students by using campus data and the symptoms of depression can also be reflected in the data, supporting scholars' behavioral models of depression [24]. This paper also provides new ideas for discovering human behavior patterns associated with depression and other mental health disorders. If combined with other types of campus data (eg, network connection event logs [60]), it is possible to achieve an artificial intelligence–based student depression prediction method.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Supplementary material for Table 5.
[XLSX File (Microsoft Excel File), 19 KB - mental_v7i1e12503_app1.xlsx]

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Abbreviations

BDI: Beck Depression Inventory
ISA: information system administrator
OR: odds ratio
SDS: Zung Self-Rating Depression Scale

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Original Paper

A Culturally Adapted Cognitive Behavioral Internet-Delivered Intervention for Depressive Symptoms: Randomized Controlled Trial

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Abstract

Background: Internet-delivered treatments for depressive symptoms have proved to be successful in high-income Western countries. There may be potential for implementing such treatments in low- and middle-income countries such as Colombia, where access to mental health services is limited.

Objective: The objective of this study was to assess the efficacy of a culturally adapted cognitive behavioral internet-delivered treatment for college students with depressive symptoms in Colombia.

Methods: This was a randomized controlled trial with a 3-month follow-up. The program comprised seven modules. A total of 214 Colombian college students were recruited. They were assessed and randomly assigned to either the treatment group (n=107) or a waiting list (WL) control group (n=107). Participants received weekly support from a trained supporter. The primary outcome was symptoms of depression, as measured by the Patient Health Questionnaire - 9, and the secondary outcomes were anxiety symptoms assessed by the Generalized Anxiety Disorder questionnaire - 7. Other measures, including satisfaction with treatment, were evaluated after 7 weeks.

Results: Research attrition and treatment dropouts were high in this study. On average, 7.6 sessions were completed per user. The mean time spent on the program was 3 hours and 18 min. The linear mixed model (LMM) showed significant effects after treatment ($t_{197.54}=-5.189$; $P<.001$) for the treatment group, and these effects were maintained at the 3-month follow-up ($t_{39.62}=4.668$; $P<.001$). Within-group results for the treatment group yielded a large effect size post treatment ($d=1.44$; $P<.001$), and this was maintained at the 3-month follow-up ($d=1.81$; $P<.001$). In addition, the LMM showed significant differences between the groups ($t_{197.54}=-5.189$; $P<.001$). The results showed a large effect size between the groups ($d=0.91$; $P<.001$). In the treatment group, 76.0% (16/107) achieved a reliable change, compared with 32.0% (17/107) in the WL control group. The difference between groups was statistically significant ($X^2_2=10.5$; $P=.001$).

Conclusions: This study was the first contribution to investigating the potential impact of a culturally adapted internet-delivered treatment on depressive symptoms for college students as compared with a WL control group in South America. Future research should focus on identifying variables associated both with premature dropout and treatment withdrawal at follow-up.

Trial Registration: ClinicalTrials.gov NCT03062215; https://clinicaltrials.gov/ct2/show/NCT03062215

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KEYWORDS

culture; internet; cognitive behavioral therapy; depressive symptoms; students; South America

Introduction

High rates of prevalence of depression have been found worldwide and in various cultural groups [1-5], with an upward trend in prevalence in low- and middle-income countries (LMICs) [6]. In South American countries such as Colombia, high prevalence rates are reported, which are similar to the prevalence rates found in high-income countries (HICs) [3,4]. In Colombia, the 12-month prevalence rate has been estimated to be between 6.6% and 10% [7].

Studies have shown that Colombia reports the second highest prevalence of major depression in Latin America after Brazil [3,8]. An epidemiological report on the prevalence of mood disorders in LMICs shows that Colombia ranks first (6.9%), compared with India (5.5%), Iraq (4.1%), Nigeria (1.2%), Beijing (2.2%), and Shenzhen (4.8%) [9]. Recently, the Pan American Health Organization and World Health Organization [10] reported that most of the South American countries have higher depression disability (7.7%), specifically Paraguay (9.4%), Brazil (9.3%), Peru (8.6%), and Colombia (8.2%). The Colombian National Mental Health Survey [11] estimated a point prevalence of mild to moderate depressive symptoms in 15.6% and severe depressive symptoms in 4.2% of adults. In addition, a report [12] shows that moderate depression among women is 70.4% compared with that among men (29.6%). Depressive symptoms can go undiagnosed and untreated, and the absence of treatment may be associated with the development of a depressive disorder [13].

Depressive symptoms are commonly reported in general populations and among college students [14-16]. Cross-cultural studies show high rates of depressive symptoms among students [17,18]. Depressive disorders are more frequent among college students in comparison with the general population [19]. For instance, a systematic review showed a 30.6% weighted mean prevalence of depression symptoms in college students from Europe, the United States, Canada, Egypt, Turkey, Korea, Lebanon, and China [20]. These rates are comparable with those from Latin American countries [21-24]. In Colombia, a study reported high prevalence of depressive symptoms (30%) in students [25]. Another recent study showed 36.2% prevalence of depression symptoms in a college sample [26]. A recent report from Colombia showed that people with university studies presented with higher levels of depression (61.6%) compared to those without a higher education (45.2 %) [12]. Several variables have been associated with the vulnerability of college students to depression: changes in lifestyle related to poor sleep habits, eating disorders, economic stressors, and family problems [20,27].

Such a high prevalence warrants implementation of interventions for depression in Colombia. However, as in many other LMICs, there are barriers for accessing mental health treatments, such as cost and coverage, that prevent people from accessing the treatments they need [11,26]. In 2016, the World Mental Health survey reported that only 6.7% of college students received treatment for their mental health disorder in LMICs [28]. Furthermore, the population with mental health problems does not have an adequate insurance coverage [11,29]. The Colombian National Mental Health Survey in 2015 showed that about 50% of the population reported that personal stigma is one of the principal reasons for not accessing mental health services, followed by geographical location and limited service availability [11].

Despite the necessity to implement psychological interventions for depression in Latin America, there are only a few studies in this field [30], more so because treatments are mostly pharmacological, and evidence-based psychological treatments are rarely used. Furthermore, most of the treatments in LMICs are implemented without considering the cultural context of the clients; very little research has investigated culturally adapted treatments [31,32], whereas there is even less research on internet-delivered treatments [33,34] that may be a suitable alternative to make evidence-based treatments available, especially when nearly 56% of the population in Colombia has access to the internet [35].

Depressive symptoms can be effectively treated with psychotherapy and pharmacotherapy [36-39]. Psychological treatments for depression have shown better outcomes than a waiting list (WL) or placebo, and combined treatment is more effective than pharmacotherapy alone [38,40]. Research has found that psychological treatments can enhance the positive effect and decrease the negative effect in depression, contributing to better outcomes [41]. A systematic review and a meta-analysis have shown that cognitive behavioral therapy (CBT) had been extensively researched and was demonstrated to be effective for depression [42,43].

Low-intensity internet-delivered treatment is usually based on cognitive behavioral principles. It involves complete or partial guidance and uses CBT techniques that are typically used in face-to-face therapy, for instance, reading passages, listening to audio files, seeing pictures, and watching animations and videos [44,45]. This type of intervention is highly structured, and it involves psychoeducation, activities, and supplementary resources such as a supporter contact via asynchronous message [46].

Internet-delivered interventions have an established empirical base for major [47] and subthreshold [48,49] depression. They are also used as maintenance treatments [50-52]. For instance, a systematic review of computer-based interventions for depression, with a supporter, found a medium-to-large (0.58-0.76) and a small-to-medium (0.25-0.36) effect size when the intervention was delivered as a stand-alone self-help treatment for the reduction of depressive symptoms, both compared with usual care [51].

Internet-delivered interventions for depression are available in many languages. Research with Spanish language versions [53] reported positive results of the effectiveness of a CBT-based internet-delivered program for depression. A recent 4-year descriptive, naturalistic study monitoring a Web-based CBT treatment developed and researched in Mexico indicated that the intervention was useful for depressive symptoms [54]. In addition, a feasibility study in Chile found a Web-based treatment to be beneficial, acceptable, and feasible [55].

For the most part, there is availability of psychological treatments and mental health services in HICs. In addition, research evidence of internet-delivered interventions and their implementation have been mainly developed in HICs [56], whereas in LMICs, most people who need mental health services do not receive any—this is known as the *mental health gap*. For instance, the World Health Organization [57] has estimated that between 76% and 85% of the people with severe mental health problems receive no treatment in LMICs. Therefore, internet-delivered interventions may be a valuable resource to reduce the treatment gap in LMICs, such as Colombia, thus ameliorating social health inequalities in these regions [58]. In addition, there is little knowledge on internet-based interventions for depression emerging in such countries [34]. A recent systematic review found that only three articles reported the results of randomized controlled trials (RCTs) in internet-delivered interventions for mental health conditions in LMICs [33].

This study aimed at evaluating the efficacy of a culturally adapted internet-delivered CBT (iCBT), *Yo puedo sentirme bien/I can feel better* program, for college students with depressive symptoms. This study is the first contribution to investigating the efficacy of an iCBT intervention in Colombia.

Methods

Study Design

The study used a randomized control design (trial registration: ClinicalTrials.gov NCT03062215) to examine the efficacy of the culturally adapted intervention in which participants were randomly assigned to two groups: (1) a culturally adapted iCBT group and (2) a WL control group.

Participants

College students from two cities and universities in Colombia were included in this study. Both undergraduate- and graduate-level students from any school at a university in Bogota City and students of psychology, medicine, nursing, and education from a university in Bucaramanga City in Colombia were eligible to participate, and they were selected according to the criteria described in Textboxes 1 and 2.

Textbox 1. Inclusion criteria.

- Age ≥18 years
- Mild to moderately severe depressive symptoms determined by the Patient Health Questionnaire - 9 scores of 10-19

Textbox 2. Exclusion criteria.

- Severe depressive symptoms: score of >19 on the Patient Health Questionnaire - 9
- Suicidal ideation or intent: score of ≥2 on question 9 of the Patient Health Questionnaire - 9
- Psychosis
- Currently in psychological treatment for depression
- On medication for <1 month
- Alcohol or drug misuse
- Previous diagnosis of an organic mental health disorder
- Depression preceding or coinciding with a diagnosed medical condition

User Recruitment

An email with information about the study and a link to access to the treatment was sent to all college students (undergraduates and postgraduates) in Bogota university and to undergraduate students studying medicine, psychology, and education in Bucaramanga university. Potential participants were able to visit a website to receive information about the study, participation criteria, treatment, and how to get in contact to proceed with the study. Recruitment took place between August 2016 and January 2017.

Procedure

Overview

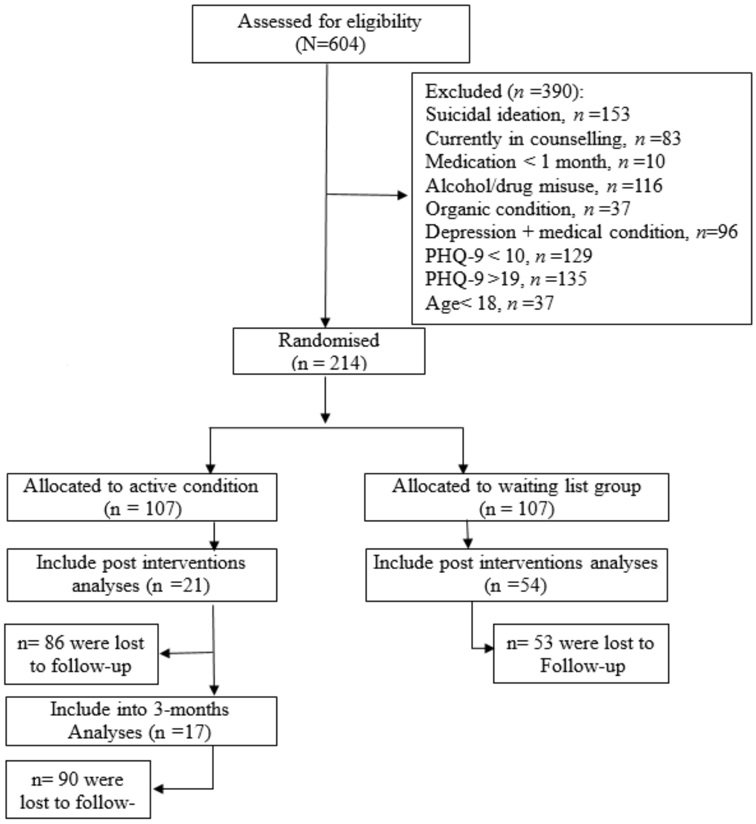
Once participants read the study information, informed consent was obtained from each user before screening and randomization. Through the SilverCloud platform, participants were instructed to type their name on the informed consent page to indicate that they had read and understood the study information and agreed to participate in the study. Thereafter, participants completed measures for screening purposes, including the Patient Health Questionnaire - 9 (PHQ-9), Sociodemographic and Clinical History Questionnaire, and Generalized Anxiety Disorder - 7 (GAD-7) questionnaire. Thereafter, participants who were eligible for the study (Textbox 1) were randomized through computer algorithms and assigned to one of two groups: the iCBT treatment and WL control groups.

Participants assigned to the active treatment group started the internet-delivered treatment immediately for 7 weeks, whereas treatment for the WL participants started after 7 weeks. Individuals not meeting the inclusion criteria at baseline assessment were referred to other appropriate sources of face-to-face support at the student counseling service in their respective universities. Once the students completed the questionnaires, they received immediate feedback on their results. If exclusion from the study was necessary, information and advice to seek counseling services at their college was provided to the student. In addition, the counseling service manager received an automatic email with information of the excluded students, their questionnaires (ie, Sociodemographic and Clinical History Questionnaire, PHQ-9, and GAD-7), and their scores. Participants received emails and calls from the research team at the posttreatment and 3-month follow-up time points to encourage them to complete their assigned measures.

Randomization

After baseline screening, eligible participants were randomized and informed immediately about their group assignment. Randomization was handled by a computer algorithm administered by a person independent of the researchers. Figure 1 shows the Consolidated Standards of Reporting Trials (CONSORT) participant flow through the trial.

Figure 1. Study participants flowchart—Consolidated Standards of Reporting Trials diagram. PHQ-9: Patient Health Questionnaire - 9.



Intervention

The Colombian iCBT program for depression assigned as treatment in this study (*Yo puedo sentirme bien*/I can feel better) is a modified version of the clinically efficacious *Space from Depression* program [59] used in Ireland and the United Kingdom. The name *Yo puedo sentirme bien* (*I can feel better* in English) was selected as a culturally appropriate descriptor for improving mood to avoid the negative connotations related to depression in Colombian culture.

The cultural adaptation that underwent several steps is described in a separate study [60]. The adaptation involved three distinct phases based on an integrative approach proposed by the author (AS). In the first phase, it involved a top-down cultural sensitivity framework, developed by the principal researcher (AS). The preliminary adaptation included work done by professional translators and an independent video company in Colombia. The first phase in the adaptation comprised a translation of the program from English to Spanish and the incorporation of cultural expressions, examples, and personal stories into the program. The second phase comprised an assessment of the preliminary program through the Cultural Relevance Questionnaire (CRQ) that was designed specifically for this study. The CRQ is based on cultural sensitivity and ecological validity theory [61] and principles from cross-cultural assessment research [60,62]. The CRQ has two sections: (1) a general assessment of the program and (2) an assessment of each module, including feedback from college students and psychology experts. The third phase involved further development of cultural incorporations into the program based on this feedback [60].

Both *Yo puedo sentirme bien* (the Colombian iCBT program used as treatment in this study) and *Space from Depression* (the original program from which it was culturally and linguistically adapted) comprise seven modules of CBT (Table 1) [63]. The treatment includes self-monitoring, behavioral activation, cognitive restructuring, and challenging core beliefs. All modules have the same structure and format, comprising quizzes, videos, educational content, and activities with homework suggestions and a module review page (Multimedia Appendices 1 and 2). Moreover, users have a supporter who provides weekly feedback asynchronously [59].

The participants accessed the intervention for free during the time of the study. They also had access to the program without a supporter for a year after the study if they wanted to use it.

Table 1. Yo puedo sentirme bien/Space from Depression program description.

Module	Brief description
Getting started	Outlines the basic premise of cognitive behavioral therapy, provides information about depression, and introduces some of the key ideas of *Space from Depression*; users are encouraged to begin to chart their own current difficulties with depression
Tune in	
I: Getting to grips with mood	The focus in this module is on mood monitoring and emotional literacy; users can explore different aspects of emotions, physical reactions, action and inaction, and how they are related
II: Spotting thoughts	This module focuses on noting and tracking thoughts; users can explore the connection between their cognitions and mood and record them graphically
Change it	
I: Boosting behavior	This module focuses on behavioral change as a way to improve mood; ideas about behavioral activation are included, and users can plan and record activities and chart their relationship with their mood
II: Challenge your thoughts	This module supports users to challenge distorted or overly negative thinking patterns, with thought records as well as helpful coping thoughts
III: Core beliefs	This module outlines the role that deeply held core beliefs could play in mood and depression; users can use a range of interactive activities to identify, challenge, and balance any unhelpful core beliefs
Bringing it all together	In this final module, users are encouraged to bring together all the skills and ideas they have gathered so far, note their personal warning signs, and make a plan for staying well

Wait List Control Group

Participants in the WL control group received treatment only after 7 weeks; therefore, this group received no treatment in the first 7 weeks of the study.

Supporters

Each of the 214 participants were assigned a supporter, who was a postgraduate student in clinical psychology with experience delivering CBT for adults. A total of 10 supporters were trained by the principal researcher (AS) to use the *Yo puedo sentirme bien/I can feel better* platform and program before starting their role as a supporter, and they were supervised by an experienced clinical psychologist at the university.

Each supporter was assigned users. Supporters provided asynchronous postsession feedback of 10-15 min per participant per week through the platform. The role of the supporter was to motivate and provide feedback to the users. The feedback was focused on improving adherence to the interventions and encouraging the application of CBT activities in the program. They scheduled the feedback at specific times, once each week for a period of 7 weeks. This schedule of support replicated what had already been implemented with the program in the Irish RCT. The messages explain how to work through the program; the supporters also suggested modules and activities to the users. All the messages were personalized, depending on the user's necessities (the content used or specific questions or comments the user made to the supporter through the platform). Further, 7 weekly automated alert messages were sent by email to all the participants, indicating that they had received a new review from their supporter.

Assessments

Through the SilverCloud platform, the assessments were completed by the participants. For the efficacy trial, participants were assessed at baseline, posttreatment, and 3-month follow-up; details of the measures are described in Table 2.

Participants were assessed at baseline using the PHQ-9, Sociodemographic and Clinical History Questionnaire, and GAD-7. At the beginning of each session, participants were asked to reflect on their previous session and complete the Helpful Aspects of Treatment Form, a qualitative measure, the results of which are not presented in this paper. PHQ-9 and GAD-7 were completed at week 7 and follow-up was completed at week 20 (3 months). A Satisfaction With Treatment (SAT) questionnaire was completed after week 7.

Table 2. Measures used (study: efficacy trial—screening and primary and secondary outcomes).

Measure	Assessed variable	Time of assessment
Patient Health Questionnaire - 9	Depression symptoms	Baseline, posttreatment, and follow-up
Generalized Anxiety Disorder - 7	Anxiety symptoms	Baseline, posttreatment, and follow-up
Sociodemographic and Clinical History Questionnaire	Gender, age, marital status, education, occupation, socioeconomic status, and clinical history	Baseline
Helpful and Hindering Aspects of Treatment>	Helpful and hindering aspects of treatment	After each session
Satisfaction	Satisfaction with the therapy	Posttreatment

Screening Measure

Sociodemographic Information and Clinical History Questionnaire

This instrument was developed on the basis of a previous version [64]. It collects data on the participants, such as the length of time one is experiencing depression symptoms; the participant's experience of counseling/therapy and medication for depression; and whether one has had a previous diagnosis of an organic mental health disorder or serious mental health disorders such as schizophrenia, psychosis, and bipolar disorder. In addition, it contains items related to comorbidity of depression, such as alcohol and drug misuse, or any recent medical diagnosis.

Outcome Measures

Primary Outcome: Patient Health Questionnaire - 9

The PHQ-9 [65] is a 9-item self-report measure that assesses the nine depression symptoms from the Diagnostic and Statistical Manual of Mental Disorders, fourth edition (DSM-IV), depression criteria. Each item is scored on a 4-point scale (0-3), and scores range from 0 to 27. The score can be used to describe a patient's symptoms in one of the five categories: none (0-4), mild (5-9), moderate (10-14), moderately severe (15-19), and severe (20-27). The PHQ-9 has been shown to have good internal reliability (Cronbach alpha=0.86-0.89) [66]. The PHQ-9 has been translated into Spanish, and a Colombian version will be used in this study. The Spanish version of PHQ-9 has also demonstrated good reliability among Latinos in the United States (alpha=.85) [67,68]. In this study, the internal consistency of the PHQ-9 in the sample was .87.

Secondary Outcome: General Anxiety Disorder - 7

The GAD-7 [69] comprises seven items measuring symptoms and severity of anxiety based on the DSM-IV diagnostic criteria. It has shown good internal reliability (alpha=.92) [70]. It has been culturally adapted into Spanish [71] and is available in a Colombian Spanish version. In this study, the internal consistency of the GAD-7 in the sample was .88.

Other Measures

Posttreatment: Satisfaction With Treatment

At posttreatment, participants were asked to complete the SAT questionnaire [72]. It asks users about positive and negative experiences with the internet-delivered treatment. It contains two questions asking participants to describe what they most and least liked about the Web-based treatment.

Data Analysis

All participants' data were included, irrespective of treatment compliance. Descriptive statistics (Chi-square and *t* tests) were used to analyze sociodemographic and clinical variables at the baseline among the groups (eg, gender and age) [73].

The effect of treatment on PHQ-9 and GAD-7 severity scores was evaluated separately for each measure by using the repeated-measures linear mixed-effects models fit with restricted maximum likelihood in the R package lme4 [74]. The core computational algorithms are implemented using the "Eigen" C++ library for numerical linear algebra and "RcppEigen glue" in the R (general public license ≥ version 2.0) [75]. Linear mixed-effects models are appropriate for analysis of longitudinal data where repeated measurements are taken from the same subjects over time and are particularly robust to missing data. All participants who provided posttreatment measures or 3-month follow-up measures, irrespective of treatment compliance, were included. Linear mixed model (LMM) fit by the restricted maximum likelihood (REML) *t* test using Satterthwaite method was employed to estimate covariance matrix, including fixed effects for time [74,76]. The REML approach is a particular form of maximum likelihood estimation that does not base estimates on a maximum likelihood fit of all the information, but instead uses a likelihood function calculated from a transformed set of data. For each measure, total scores were modeled using fixed effects of time, treatment group and the interaction between time and treatment group, and a random effect of individual/identification. The significance of each fixed effect was evaluated with *t* tests using the Satterthwaite degrees of freedom method [77]. Post hoc pairwise comparison of means estimated from the models were performed using the R package. All reported *P* values are two-tailed, with significant levels at $P<.01$, $P<.01$, and $P<.05$. The magnitude of the treatment effect within and between the two groups was assessed using the Cohen *d* statistic [73]. Cohen describes an effect size of 0.2 as small, 0.5 as medium, and 0.8 as large [78].

Analyses were conducted to assess how many participants achieved clinically significant changes at the end of the intervention and at follow-up. The assessments were made through a comparison of pretreatment scores with posttreatment and follow-up scores on the outcome measures PHQ-9 and GAD-7. Reliable change was assessed using the Jacobson and Truax reliable change criteria. Internal consistency, measured with Cronbach alpha, was used as the reliability estimate, and it was high for both the PHQ-9 (alpha=.89) and GAD-7 (alpha=.88). Change on either measure was considered reliable if it exceeded the resulting reliable change index, which was calculated to be 3.98 for the PHQ-9 and 3.61 for the GAD-7. Reliable recovery criteria were calculated as the combination of the reliable change index (RCI) and cutoff score and the percentage of participants who achieved a posttreatment score of ≤10 on the PHQ-9 and ≤8 on the GAD-7.

Descriptive statistics were used to analyze the quantitative data from the SAT questions, and the qualitative responses from this questionnaire were analyzed using thematic analysis. The categorization of data followed that identified in the previous research [79].

Ethics

The research project and all related materials were submitted and approved by the appropriate university ethics committees in Colombia. Participants were provided with the study information including the aims and objectives and provided informed consent. Participants meeting exclusion criteria were referred to other appropriate sources of support at the universities. The study protocol, information on the study, informed consent, and related materials were submitted and approved by the ethics committee of the two universities.

Results

Baseline Characteristics

Descriptive statistics revealed that at postrandomization, there were no significant differences in the sample between the iCBT and WL control groups on any variables. Table 3 shows details of the characteristics of the sample. The mean age was 22.15 (SD 4.74) years. All the participants were full-time students. The majority of the college student sample was from health sciences (86/214, 40.2%), followed by social sciences (62/214, 29.0%), and engineering (37/214, 17.3%).

There was no significant difference between the proportions of participants who reported a previous diagnosis of depression in the control group versus the treatment group. The majority of the participants reported depressive symptoms of between 1 and 2 years (35.0%, 75/214). Of the participants, 21.9% (47/214) reported to have had counseling/psychotherapy for depression in the past. Finally, the sample reported confidence in their use of information technology (IT), with 33.6% (72/214) of participants reporting feeling confident. Of the participants, 40.6% (87/214) reported feeling not so confident using technology.

Table 3. Demographic and clinical variables.

Variable	Total (N=214), n (%)	Treatment (N=107), n (%)	Control group (N=107), n (%)	*P* value
Gender				**.56**
Female	153 (71)	74 (69.2)	79 (73.8)	
Male	61 (28.5)	33 (30.8)	28 (26.2)	
Age (years)				
Mean (SD)	22.15 (4.7)	22.24 (5.4)	22.06 (3.9)	.98
Range	N/A[a]	18-52	18-37	—
Education subject				**.81**
Health sciences	86 (40.2)	46 (43.0)	40 (37.4)	
Social sciences	62 (29.0)	31 (29.0)	31 (29.0)	
Engineering	37 (17.3)	17 (15.9)	20 (18.7)	
Postgraduate subjects	29 (13.6)	13 (12.1)	16 (15.0)	
Time with symptoms				**.31**
<6 months	56 (26.1)	28 (26.2)	28 (26.2)	
1-2 years	75 (35.0)	42 (39.3)	33 (30.8)	
2-5 years	43 (20.0)	22 (20.6)	21 (19.6)	
>5 years	40 (18.6)	15 (14.0)	25 (23.4)	
Previous therapy for depression				**.32**
Yes	47 (21.9)	20 (18.7)	27 (25.2)	
No	167 (78.0)	87 (81.3)	80 (74.8)	
Previous medication for depression				**.72**
Yes	37 (17.2)	20 (18.7)	17 (15.9)	
No	177 (82.7)	87 (81.3)	90 (84.1)	
Current medication for depression				**>.99**
Yes	7 (3.2)	3 (18.7)	4 (15.9)	
No	207 (96.7)	104 (81.3)	103 (84.1)	
Information technology–related confidence				**.02**
Very confident	6 (2.8)	2 (1.9)	4 (3.7)	
Confident	72 (33.6)	35 (32.7)	37 (34.6)	
Average	4 (1.8)	2 (1.9)	2 (1.9)	
Mildly confident	72 (33.6)	52 (23.4)	20 (18.7)	
Not confident	87 (40.6)	43 (40.2)	44 (41.1)	

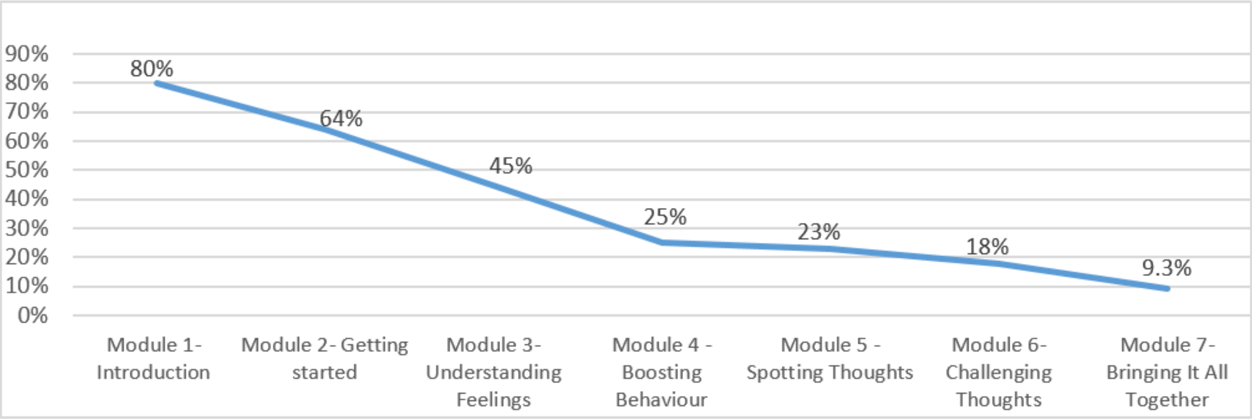
[a] Not applicable.

Treatment Response Rate

Participants were offered 7 modules to complete. Similar to the original efficacy trial, although they were instructed to complete each of the 7 modules, the choice, pace, and control over the direction and dose of their engagement was entirely up to them [59]. Of the 107 participants randomized to the immediate treatment group, 80% (86/107) began module 1, and 9.3% (10/107) completed all modules. Figure 2 represents the treatment response rate over time.

A session in a Web-based intervention is defined as an instance when a client logged into the system [59]. Session time estimation is not exact because users may be interrupted or take breaks within a session and may not formally log out of the system. Regarding the treatment group, the total number of sessions completed was 734, with an average of 7.6 sessions completed per user. The mean time spent on the program was 3 hours and 18 min.

Figure 2. Percentage of users accessing modules over time.



Research Data Attrition

A total of 604 participants were screened, of which 390 were excluded based on the established criteria. A significant number of participants were excluded because of suicidal ideation (153/604, 25.3%) and misuse of drugs or alcohol (116/604, 19.2%). At sign-up, there were a total of 107 participants assigned to the treatment group and 107 assigned to the WL control group. See CONSORT flow in Figure 1.

The Little´s Missing Completely at Random (MCAR) test revealed a nonsignificant result (X^2_4=1.28; *P*=.86), indicating that the data were missing completely at random [80]. The percentage of participants who completed research measures at postintervention was 19.6% (21/107) and the 3-month follow-up was 16.8% (18/107). In the WL group, the response was higher, with 50.4% (54/107) of participants present at the postintervention assessment. The WL control group was not followed up beyond this point, as they entered treatment.

Intention-To-Treat Analysis

Owing to the very high percentage (86/107, 80.3%) of missing data in the sample, we decided not to follow the protocol data analysis strategy [63]. Instead, we modified our approach to include only those participants who provided posttreatment measures (21/107, 19.6%) or the 3-month follow-up (18/107, 16.8%) measures.

Patient Health Questionnaire - 9

The iCBT and WL control group samples were compared using LMMs, adjusting for depression and anxiety scores in the model. LMM including fixed effects for time showed significant effects after treatment ($t_{38.23}$=−5.079; *P*≤.001) within the iCBT treatment group. The effects were also maintained at the 3-month follow-up ($t_{39.62}$=−4.668; *P*≤.001) for the treatment group (see Table 4). Also, LMM shows significant differences between the groups ($t_{197.54}$=−5.189; *P*≤.001) in favor of the treatment group.

The within-group results for the treatment group yielded a large effect size after treatment (*d*=1.44; *P*≤.001), and this was maintained at the 3-month follow-up (*d*=1.81; *P*≤.001). Similarly, the results showed a large effect size between groups (*d*=0.91; *P*≤.001). Figure 3 provides a graphical representation of the changes in depressive symptoms between groups pre- and posttreatment.

Table 4. Descriptive data for the Patient Health Questionnaire - 9 and Generalized Anxiety Disorder - 7 by group over time (intention to treat).

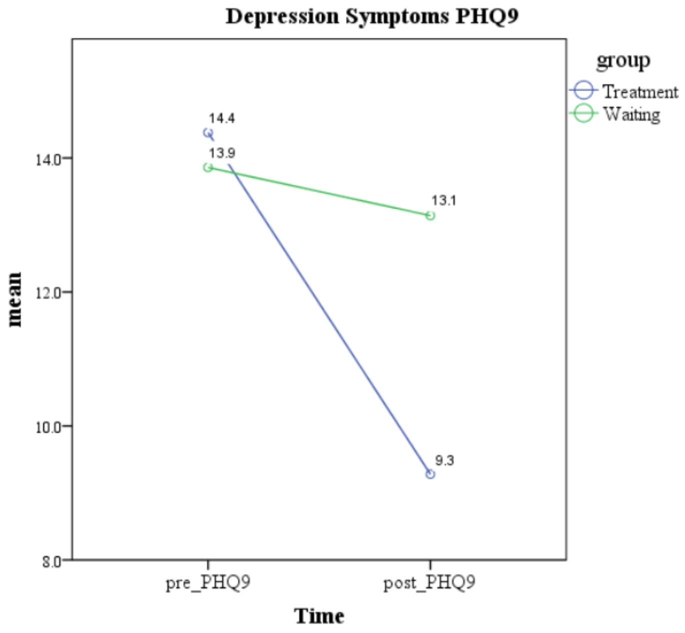
Outcome measures	Treatment							Follow-up				
	Baseline		Pretreatment		Posttreatment		Within-group effect size (95% CI)	Baseline		3-month follow-up		Effect size (95% CI)
	t (*df*)	*P* value[a]	n	Mean (SD)	n	Mean (SD)		*t* (*df*)	*P* value[b]	n	mean (SD)	
Patient Health Questionnaire - 9												
Treatment group	−5.079 (38.23)	≤.000	107	14.22 (2.81)	21	8.33 (5.71)	1.44 (0.38 to 2.49)	−4.668 (39.62)	≤.000	17	8.41 (5.98)	1.81 (0.69 to 2.92)
Waiting list group	N/A[c]	N/A	107	13.82 (2.93)	54	13.09 (5.06)	0.20 (−0.78 to 0.58)	N/A	N/A	N/A	N/A	N/A
Generalized Anxiety Disorder - 7												
Treatment group	−2.632 (37.83)	≤.012	107	10.56 (4.380)	21	7.19 (4.79)	0.73 (0.08 to 1.37)	−2.486 (38.88)	≤.017	17	7.83 (6.23)	0.52 (−0.17 to 1.21)
Waiting list group	N/A	N/A						N/A	N/A	N/A	N/A	N/A

[a] Compared to posttreatment.

[b] Compared to the 3-month follow-up.

[c] Not available.

Figure 3. Changes in depression symptoms pre- to postintervention. PHQ-9: Patient Health Questionnaire - 9.

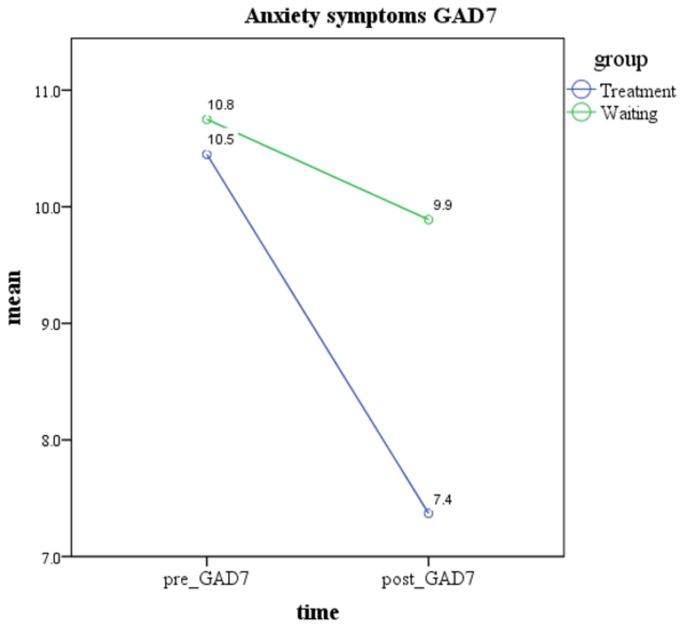


Generalized Anxiety Disorder - 7

Similarly, the iCBT group and WL control group samples were compared using LMM. Within the iCBT group, time point was a significant predictor of the GAD-7 score, with a significant effect from baseline to posttreatment ($t_{37.83}$=−2.632; *P*≤.012) and the 3-month follow-up ($t_{38.8}$=−2486; *P*≤.017; Table 4) within the treatment group. The interaction effect was also significant, representing significant differences in the GAD-7 score change observed from baseline to posttreatment between the groups ($t_{103.53}$=−2.229; *P*≤.03) in favor of the treatment group.

The within-group results for the treatment group yielded a medium-to-large effect size after treatment (*d*=0.73; *P*≤.001), and this was maintained at the 3-month follow-up (*d*=0.52; *P*≤.001). The mean scores indicated that the treatment group reported significantly lower levels of anxiety symptoms after treatment than those in the WL control group, yielding a medium posttreatment effect size between the groups for the intervention (*d*=0.60; *P*≤.001). Figure 4 provides a graphical representation of the changes in anxiety symptoms between groups.

Figure 4. Changes in anxiety symptoms pre- to postintervention. GAD-7: Generalized Anxiety Disorder - 7.



Clinically Significant and Reliable Change

RCI values were calculated in this sample population. For the PHQ-9, change was needed to exceed the RCI value of 3.97, and for the GAD-7, a value of 3.63, to be considered reliable. The proportion of each group that showed reliable improvements (or deterioration) between baseline and posttreatment and the 3-month follow-up was determined using these reliable change criteria. The analysis included only the number of participants who provided follow-up measures.

In the iCBT group, 76% (n=16) achieved reliable change, compared with 32% (n=17) in the WL control group. The differences between groups were statistically significant (X^2_2=10.519; *P*=.001). Reliable recovery from depression and anxiety was established by identifying the RCI and the percentage of participants who achieved a posttreatment score of ≤10 on the PHQ-9 and ≤8 on the GAD-7. In the iCBT group, 10 (n=10) participants met the criteria for reliable recovery on depression symptoms and 9 (n=9) met the criteria for the same on anxiety symptoms.

Satisfaction With Treatment

After 7 weeks, the participants (n=40) also completed the SAT questionnaire. Most of the users were happy to use a computer to access their treatment (76%, n=30) and found the interventions easy to use (82%, n=32). Furthermore, the majority of participants (68%, n=27) found the Web-based treatment helpful (Table 5).

Table 5. Results from the Satisfaction With Treatment questionnaire, (n=40).

Questionnaire items	Participants		
	Agree (%)	Disagree (%)	Neither (%)
I was happy to use the computer to access the treatment	76	8	16
I found the intervention easy to use	82	5	13
I feel the treatment received will have a lasting effect	63	8	29
I would recommend the Web-based treatment to others	68	16	16
How helpful you found the Web-based treatment program	68[a]	23[b]	10[c]

[a] Helpful.

[b] A little helpful.

[c] Not at all helpful.

The final two questions in the satisfaction measure were qualitative and asked participants what they most and least liked about the Web-based treatment. The majority of the users reported its accessibility and flexibility (n=20, 50%) as the aspects they liked the most. The other aspects liked were the applicability of the program to their life, having a supporter, and the interactive tools and the activities:

> *The availability of all the material that it includes and the sense of security that it gives to know that I can receive help at any time.*
>
> *The strategies proposed are very effective that allows us to question about the [negative] habits have [are unhelpful] to lead a happier life.*

> *...That I could keep track of my emotions and moods.*

When asked what they *least liked* about the Web-based treatment program, some participants reported that the program did not meet their individual needs, such as immediate feedback or synchronic interaction with the supporter (n=11, 28%) and lack of time (n=4, 10%).

> *The platform is impersonal. Perhaps, it was not what I needed to hear. Perhaps, nothing replaces being in touch in real life with someone.*

Discussion

Principal Findings

The study aimed at evaluating the efficacy of a culturally adapted *Yo puedo sentirme bien/I can feel better* program for college students with depressive symptoms in Colombia**.** The results show a very high research attrition and treatment dropout in this sample. However, the treatment group demonstrated statistically significant decreases in depressive symptoms from baseline to posttreatment, relative to the pre-post change in the WL control group, and this reduction in symptoms was maintained at the 3-month follow up. Furthermore, a significantly larger proportion of the iCBT group achieved a reliable change, compared with the WL control group. The results from this study thus showed that the culturally adapted cognitive behavioral internet-delivered program, *Space from Depression*, is effective in reducing depressive symptoms in comparison with a WL control group. These results support previous research findings on the *Space from Depression* program in Ireland [59]. The findings presented here indicate that the program can potentially be used with other cultural groups, provided that it is modified to contain culturally adapted components.

The results in this study also showed that positive changes in depressive symptoms can be maintained by users at the 3-month follow-up. This is a relevant finding regarding maintenance of gains achieved from an internet-delivered intervention. Previous research [81,82] in culturally adapted internet interventions for depression with Arab and Chinese immigrants has been consistent in demonstrating lasting effects. For instance, a study [81] found that a reduction in depressive symptoms was still maintained at the 3-month follow-up within a population of Chinese immigrants.

Furthermore, this study found that the *Yo puedo sentirme bien/I can feel better* program is effective in reducing comorbid symptoms of anxiety in comparison with a WL control group. Statistically significant reductions were observed in anxiety symptoms for the intervention group from pre- to posttreatment, and these were maintained at the 3-month follow-up. The results support the efficacy of this internet-delivered cognitive behavioral intervention for depression and anxiety, as has been observed in a previous study of the intervention in English [59]. Similarly, a study [83] showed a significant reduction in depression and comorbid anxiety after treatment and at the 3-month follow-up in an RCT with Turkish immigrant residents in the Netherlands.

This RCT reports the results from the first culturally adapted internet-delivered program with asynchronous Web-based support in an LMIC in South America. The intervention showed similar outcomes to those established previously in Web-based treatments for depression and anxiety in HICs [51,59,84-86]. The evidence base for internet-delivered interventions for depression and anxiety symptoms comes mainly from people living in developed countries [56], whereas iCBT may be a valuable resource to reduce the treatment gap for those living in less developed countries, thus ameliorating social health inequalities between regions [58].

Furthermore, a reliable change was achieved by a greater percentage of those in the iCBT group (n=16, 76%), compared with those in the WL control group (n=17, 32%). The reliable change in internet-delivered interventions has showed greater percentage in different studies in the literature based on intention-to-treat (ITT) samples. For instance, a study of culturally adapted iCBT for depression reported a reliable change in the treatment group (32%) as measured using the Center for Epidemiological Studies-Depression [83]. In addition, a culturally adapted transdiagnostic iCBT for depression and anxiety [87] reported that participants made a 50% greater improvement on the PHQ-9 at posttreatment and the 3-month follow-up, respectively, using a posttreatment score at or below the clinical cutoff on the PHQ-9 (≥10) as a criterion for reliable change. A study of the internet-delivered treatment for depression upon which this cultural adaptation is based, the *Space from Depression* program, reported a 31% reliable change in the treatment group by using a criterion of change of ≥9 points on the Beck Depression Inventory-II from pre- to posttreatment [59].

The participants in the iCBT group spent an average of 3 hours and 18 min using the treatment and an average time of 18.2 min per session. Participants determined the amount of time they spent on the platform, which is a feature of internet-delivered interventions. A research study using the *Space from Depression* program with a sample from the general population in Ireland showed a greater mean time spent on the program in this population (5 hours 22 min) [59]. This difference in time spent using the intervention could be associated with time limitations within the college student sample in Colombia, where exam weeks and academic tasks can affect people's use of the program. This time limitation among college students may have also compromised the success of the intervention (ie, the high dropout). Studies have identified factors that could influence the time spent on the Web, such as processing speed, cognitive ability, reading aptitude, and familiarity using computers [88].

High Levels of Depressive Symptoms and Suicidal Ideation

Both colleges reported high exclusion criteria at the beginning (64% of participants were excluded before they were randomized to treatment and WL control groups). For instance, in Bogota, a high proportion of students were excluded because of suicidal ideation (n=130, 24%) and drug/alcohol misuse (n=94, 17%). Similarly, in Bucaramanga, a high proportion of students reported suicidal ideation (n=23, 12%) and alcohol and drug misuse (18%, n=22). The exclusion might be considered higher compared with other studies in HICs [53,59,89]. In culturally adapted internet-delivered treatment for depression, high exclusion rates related to suicidal ideation have been reported in different populations [81,83]. Studies have supported that the reasons for the exclusion may include different interpretations that communities have about mental disorders that may not be considered in the measures used for depression [2,90]. More studies are needed in this area to develop validated measures considering cultural differences. In addition, college students typically report a higher prevalence of depression, suicidal ideation, and alcohol/drug misuse [20,28], and there are similar reports in South America [26,91].

Furthermore, the iCBT program was tested for mild-to-moderate depressive symptoms, which shows the necessity of its use in higher levels of depression or more precise measures to assess participants with more significant levels of depression, given how common it was for people to be screened out for psychological symptoms. The *Space from Depression* program has also reported efficacy with this population [92]; future studies should be considered at this point.

Attrition

Research Attrition

In this study, only 20% of the participants completed measures after treatment and 17% completed them at the 3-month follow-up. This very high attrition is not easily comparable with other culturally adapted internet-delivered treatment for depression studies. For instance, a study [83] showed that 58% participants completed the posttreatment measures (6 weeks), and 38% filled the follow-up assessment at 4 months. In addition, Choi et al [81] reported that 92% of the users completed the posttreatment questionnaires, and 84% of participants completed the questionnaires at the 3-month follow-up. Internet-delivered interventions for depression have showed higher retention rates, for example, a study [93] reported 49% of participants providing data at posttreatment and 35% at follow-up. In a previous study using the *Space from Depression* program, 63% of participants completed measures after treatment (8 weeks), and 52% completed 3-month follow-up measures [59]. Procedural variables could be associated with the very high research attrition rate in this study, such as phone numbers of the participants not being available from the beginning of the study and limiting phone calls to the participants to encourage them to complete the measures after treatment.

In this study, recruitment was conducted by email, and therefore, there was no face-to-face contact with the participants. Personal contact at the beginning of the intervention would have, perhaps, encouraged the participants' engagement and continuation with the program. This is also associated with another factor linked to attrition—lack of reminders [94]. In this study, users received emails and calls at the end of the study to encourage them to complete the measures. Some limitations were present, such as the calls being made from Ireland, where there is a significant time difference with Colombia. Therefore, it was not possible to call the participants during a specific time that they might be more likely to answer the phone. Moreover, it is likely that for some participants, reminder emails went to spam. Studies have suggested personality factors, cognitive abilities, and motivation as relevant determinants for attrition [95]. We did not evaluate these elements in this study. Future studies should examine strategies to decrease attrition rates, which is a determinant of effectiveness in internet interventions.

Treatment Dropout

Only a small proportion of participants completed all modules; 80% (86/107) of the participants in the iCBT group began with module 1, and 9% (10/107) completed all modules. Treatment dropout has been found to be a problem in internet interventions [94,96]. However, studies have shown that having a supporter is associated with higher engagement and efficacy in Web-based interventions [51,97]. Unfortunately, that was not the case in this study. Despite the training provided to the supporters in the Web-based program and their experience in CBT, the population engagement was low. The possible reasons could include barriers related to accessing mental health treatments in Colombia, such as lack of motivation for change, negative perception of psychological treatments, and personal stigma [26]. In addition, this is the first study with internet-delivered interventions in Colombia and in South America, which might affect the engagement with the treatment.

Furthermore, possible cultural differences and specific characteristics of the college student sample could be considered in future studies in Colombia to try to improve engagement with the treatment. For instance, the structure of the year and competing demands on students, for example, exams and holiday periods, can have a detrimental impact on engagement and adherence to any intervention. In addition, a lack of reminders has been associated with participant dropout [94]. In this study, participants received an automatic alert email each week from their supporter. It is probable that these automatic alerts were received as spam, and consequently, the participants could have forgotten to use the program and dropped out from the intervention. In addition, 87 participants (41%) of the population in this study reported low IT confidence, which could be another dropout factor and may affect engagement with the intervention [98]. Studies have associated the low use of technology with attrition in Web-based interventions [95]. Future studies could assess and develop strategies to support participants with low IT confidence. Activities could involve training and calling the participants to clarify or guide them on how to use the internet intervention. Despite the fact that the *Space from Depression* program involves interactive videos and information on how to explore the program, the supporter could also reinforce and guide the user with this as part of the weekly feedback. Considering these points, the analysis also revealed that participants who completed posttreatment measures showed higher program usage (mean number of logins 11, SD 7.32), compared with those who did not (mean number of logins 3.28, SD 2.76). These outcomes may be reflective of the low IT confidence reported by the sample.

In addition to this inexperience with IT, the intervention was implemented into a sample largely inexperienced in using counseling. Only 20% of the participants in this study had received psychotherapy previously, which could be considered another factor for dropping out. It also highlights the opportunity the study provided for these populations to have access to a treatment program for depression, showing the potential of iCBT to reach different, typically inaccessible, populations.

Satisfaction With Treatment

The results from the satisfaction and user-experience questionnaires indicated that, in general, participants were satisfied with accessing an iCBT intervention. However, a minority of participants felt the treatment did not meet their individual needs, as they found it difficult to get motivated and engage with the program. Flexibility and accessibility were most liked by the participants, which is consistent with previous studies [72,79]. Participants found the intervention easy to use and were happy to access the Web-based treatment. It should be noted that the SAT response rate was low and might be biased toward those who were satisfied with the program and found it helpful.

One of the most significant aspects reported by the participants was presence of a supporter. Having a supporter was valuable to encourage the user to continue with the program and provided guidance and feedback. Some participants reported feeling relieved because of the supporter or having a space to express themselves. All the participants in this study reported positive comments about their supporters, which may reflect the importance of having a trained postgraduate student as an appropriate component to provide suitable feedback to the users. However, a limited number of users share information with their supporter, reflecting a sense of anonymity unique to a Web-based treatment [99].

Participants reported aspects of time as something they least liked about the internet-delivered intervention, which was related to difficulties in completing all the modules in the program. Users reported a lack of time because of academic commitments or personal circumstances. Participants also reported that they did not have enough time to complete the modules in the program and feeling rushed to review the content between sessions. Similar findings have been reported previously [79].

Strengths of the Research

First, the results show that the culturally adapted program *Yo puedo sentirme bien/I can feel better* was effective in reducing depressive symptoms and comorbid anxiety symptoms with college students in Colombia. The original *Space from Depression* program has been previously investigated with college students [100] and a community population [59], with significant improvement in depressive symptoms pre- to posttreatment in both populations. Most of the studies of internet-delivered interventions have been studied in HICs, which might not be generalizable to other populations worldwide. Therefore, knowing more of the effectiveness of internet interventions in LMICs may mean that this type of treatment can be an alternative for people who cannot access mental health services because of limited health insurance or personal stigma and is therefore relevant in Colombia [11,101].

Second, despite the high attrition rate found in this study, this type of treatment was an opportunity for students to have access to a psychological intervention. A recent report showed that only a small minority of college students receive adequate treatment for their mental disorders in low-income countries (6%), compared with HICs (23%) [28].

Third, this study adds supporting evidence for using trained student supporters in guided internet-delivered interventions for mild-to-moderate depressive symptoms. Several studies have reported that various levels and type of supporters can achieve positive outcomes in low-intensity internet-delivered interventions for depression [51,85]. Despite the high dropout rate in this study, the student supporters in the study might play an important role in increasing engagement with the program. Corroborating this, qualitative comments by the participants on the SAT were positive about the interaction with their supporters.

Finally, this type of intervention could be delivered through a counseling service with trained students in Colombia. Similarly, it may be employed as a potential alternative in primary care or other populations. Studies have evidenced that internet-delivered interventions might potentially reduce the barriers to treatment access in LMICs [30]. In addition, culturally adapted internet-delivered treatments could reduce cost and possibly personal stigma [102]. Therefore, the study alludes to the potential of a culturally adapted internet-delivered intervention, with support, to accomplish significant outcomes. In locations where mental health services are underdeveloped, health care structures do not exist, or there is a potential to offset risk and escalation of difficulties and benefit from early intervention, such a model of service provision could be feasible [103].

Limitations

A noted limitation is that the study did not include an official depression diagnosis of participants; however, it includes well-established measures of symptom severity that can allow us to establish the efficacy of low-intensity internet-delivered treatments for depression symptoms among college students in Colombia. Another concern is with regard to the problem of missing data.

Owing to the high attrition of research data, it would not have made sense to complete a true ITT analysis including appropriate imputation of missing values. Therefore, our ITT analysis is not as robust as we would have liked, and as a result, caution is advised in any interpretation of the results from this study.

The research attrition was high at posttreatment, and it was even higher at the follow-up. Reminders in the form of emails were sent (maximum four times) and phone calls were made with some participants who provided their contact details (maximum three times), but this did not result in a significant decrease in study dropout/attrition rate. The reasons for this high attrition rate are not entirely known. In addition, the cultural adaptation of the program was not further evaluated after the intervention with the participants, which might have allowed us to assess and identify potential factors related to the adaptation that could have affected dropout.

Future Research

Internet-delivered interventions for depression have shown significant effects post treatment [51], specifically, in high-income Western countries. LMICs around the world have scarce access to mental health services [26]. A strategy to utilize the internet to provide more widely available and low-cost mental health care has vast potential. In addition, internet-delivered treatments could contribute to the globalization of mental health services and psychological interventions, for which cultural adaptation is the key [33].

This study was the first contribution regarding the potential impact of a culturally adapted internet-delivered, low-intensity intervention on depressive symptoms for college students, as compared with a WL control group, in South America. Internet-delivered interventions could be a potential option for delivering evidence-based psychological interventions and may overcome some of the significant barriers to accessing mental health treatment in Colombia. Future research should focus on monitoring participants who drop out prematurely from the study at a follow-up to evaluate the reasons for withdrawal.

This study has demonstrated the potential for internet-delivered interventions to provide satisfactory, acceptable, and effective low-intensity treatments to individuals living with depression in South America. The accessibility and flexibility unique to a Web environment may increase the access to mental health interventions around the world, considering the cultural characteristics of the populations, and this may contribute to decreasing the mental health treatment gap in LMICs.

In future studies, analysis of the central characteristics of the sample, such as age, previous level of depression, familiarity with the technology, previous treatments, and the perceived usefulness of the treatment, among others, could show the extent to which different groups of people might benefit more from this type of Web-based treatment. In attempting to explain and understand the reasons for dropout in the sample, a number of reasons were speculated upon. However, future studies might analyze further the population’s previous knowledge about depression, any associated personal stigma, and their perception of how psychological treatment could help overcome it.

Conclusions

This study showed that the culturally adapted iCBT program *Yo puedo sentirme bien*/*I can feel better* could be employed in different cultural groups as a population-level intervention for mild-to-moderate symptoms of depression. Importantly, outcomes from the treatment group were maintained at the follow-up. The research attrition was high at posttreatment and at the follow-up in this study. Future research should focus on monitoring participants who drop out prematurely from the study at a follow-up to evaluate the reasons for withdrawal. The results from this study are encouraging for the implementation of the culturally adapted internet-delivered cognitive behavioral program, *Space from Depression*, for the treatment of depression symptoms in a culturally different population, helping disseminate evidence-based treatments in LMICs.

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Authors' Contributions

AS is the principal investigator of the research. AS, DR, and LT conceptualized the initial trial design. The manuscript was written by AS, with significant contributions and revisions from DR, LT, SC, and LC. SC also contributed to the data analysis. Both MM and YP contributed to the design of the study through their contribution as site-specific investigators, and they reviewed the final version of this manuscript. AS distributed the manuscript to the group for discussion and revisions. The finalized manuscript was agreed upon by all authors.

Conflicts of Interest

AS was the recipient of an IRC scholarship award [EPSPG/2014/98] under the Enterprise/Academia collaboration scheme with SilverCloud Health. From March 2018 to March 2019, AS was a part-time employee in SilverCloud Health. DR is the Chief Science Officer at SilverCloud Health. LT provides a research consultancy for SilverCloud Health. SC worked as a data analyst at SilverCloud Health.

Multimedia Appendix 1
Screenshot of the Space from Depression program.
[PNG File , 119 KB - mental_v7i1e13392_app1.png]

Multimedia Appendix 2
Tools - Space from Depression program.
[PNG File , 186 KB - mental_v7i1e13392_app2.png]

Multimedia Appendix 3
CONSORT-EHEALTH checklist (V 1.6.1).

[PDF File (Adobe PDF File), 2436 KB - mental_v7i1e13392_app3.pdf]

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Abbreviations

CBT: cognitive behavioral therapy
CONSORT: Consolidated Standards of Reporting Trials
CRQ: Cultural Relevance Questionnaire
DSM IV: Diagnostic and Statistical Manual of Mental Disorders, fourth edition
GAD-7: Generalized Anxiety Disorder - 7
HIC: high-income country
iCBT: internet-delivered cognitive behavioral therapy
IRC: Irish Research Council
IT: information technology
ITT: intention-to-treat
LMIC: low- and middle-income country
LMM: linear mixed model
PHQ-9: Patient Health Questionnaire - 9
RCI: reliable change index
RCT: randomized controlled trial
REML: restricted maximum likelihood
SAT: Satisfaction With Treatment
WL: waiting list

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Original Paper

Web-Based Graphic Representation of the Life Course of Mental Health: Cross-Sectional Study Across the Spectrum of Mood, Anxiety, Eating, and Substance Use Disorders

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Abstract

Background: Although patient history is essential for informing mental health assessment, diagnosis, and prognosis, there is a dearth of standardized instruments measuring time-dependent factors relevant to psychiatric disorders. Previous research has demonstrated the potential utility of graphical representations, termed *life charts*, for depicting the complexity of the course of mental illness. However, the implementation of these assessments is limited by the exclusive focus on specific mental illnesses (ie, bipolar disorder) and the lack of intuitive graphical interfaces for data collection and visualization.

Objective: This study aimed to develop and test the utility of the Tulsa Life Chart (TLC) as a Web-based, structured approach for obtaining and graphically representing historical information on psychosocial and mental health events relevant across a spectrum of psychiatric disorders.

Methods: The TLC interview was completed at baseline by 499 participants of the Tulsa 1000, a longitudinal study of individuals with depressive, anxiety, substance use, or eating disorders and healthy comparisons (HCs). All data were entered electronically, and a 1-page electronic and interactive graphical representation was developed using the Google Visualization Application Programming Interface. For 8 distinct life epochs (periods of approximately 5-10 years), the TLC assessed the following factors: school attendance, hobbies, jobs, social support, substance use, mental health treatment, family structure changes, negative and positive events, and epoch and event-related mood ratings. We used generalized linear mixed models (GLMMs) to evaluate trajectories of each domain over time and by sex, age, and diagnosis, using case examples and Web-based interactive graphs to visualize data.

Results: GLMM analyses revealed main or interaction effects of epoch and diagnosis for all domains. Epoch by diagnosis interactions were identified for mood ratings and the number of negative-versus-positive events (all P values <.001), with all psychiatric groups reporting worse mood and greater negative-versus-positive events than HCs. These differences were most robust at different epochs, depending on diagnosis. There were also diagnosis and epoch main effects for substance use, mental health treatment received, social support, and hobbies (P<.001). User experience ratings (each on a 1-5 scale) revealed that participants found the TLC pleasant to complete (mean 3.07, SD 1.26) and useful for understanding their mental health (mean 3.07, SD 1.26), and that they were likely to recommend it to others (mean 3.42, SD 0.85).

Conclusions: The TLC provides a structured, Web-based transdiagnostic assessment of psychosocial history relevant for the diagnosis and treatment of psychiatric disorders. Interactive, 1-page graphical representations of the TLC allow for the efficient communication of historical life information that would be useful for clinicians, patients, and family members.

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KEYWORDS

mental health; life history; psychosocial factors; depression; anxiety; substance use disorders; eating disorders

Introduction

Background

Understanding the longitudinal course of mental health is crucial for guiding the clinical conceptualization of mental illness [1]. Psychosocial history is particularly important for illuminating environmental, psychological, and biological factors that may influence an individual's course of illness. Yet, it is one that psychiatry has struggled to adequately and effectively integrate into explanatory models [2-4]. Current assessments of psychosocial history often rely on unstructured methods, such as open-ended interviews. With the advent of electronic medical records, some clinicians and/or health systems have adopted more structured approaches; however, there remains variability in the quality and type of information contained. Such variability stands in contrast to standardized self-report and diagnostic assessments [5,6], potentially neglecting a nuanced understanding of individual patients in the clinic as well as grouped samples in research studies.

One approach for capturing the complexity of an individual's illness course is to depict it graphically. Post et al [7] developed the National Institute of Mental Health (NIMH) Life Chart method, involving pictorial demonstrations of manic and depressive episodes of individuals with bipolar disorder [8]. In this approach, data gathered from patient and collateral interviews were incorporated into a visual chart organized according to a chronological timeline, with illustrations of pertinent events (eg, suicide attempts, hospitalizations, and medication changes) and illness severity on a perpendicular axis. The resulting chart consisted of a single image containing the majority of outcomes perceived to be pertinent to their illness course. This material, intended to be shared with the patient, family members, or clinicians, was thought to (1) succinctly identify and communicate the emergence of certain patterns in their illness trajectory, (2) assist therapeutic management decisions via an explicit observational measure (eg, similar to monitoring of blood glucose levels in an individual with diabetes), (3) enhance the psychotherapeutic process by increasing insight into these patterns, and (4) improve continuity of care when transitioning from 1 clinician or health system to another. Life history interviews used in other mental health populations (without graphical representations of data collected) have also been found to increase the detection and diagnosis of mental health disorders [9,10].

Despite the apparent advantages of structured and graphical life history methods, this approach has not been widely adopted within the mental health field mainly because of the amount of time required to collect such information and the technological resources needed to develop software with an intuitive graphical interface. In addition, most existing measures focus exclusively on bipolar disorder, with little regard to the high levels of comorbidity across diagnostic categories [11], healthy/resilient populations [12], or relevant psychosocial contexts (eg, social supports, traumatic events, employments, educational history, or stability of home environment) [13]. Furthermore, current assessments do not readily provide an intuitive graphic representation for clinicians, patients, and family members to gain insight into the individual's unique psychosocial history.

Objective

Inspired by the NIMH Life Chart approach for bipolar disorder, the primary goals of this study were to (1) develop a structured approach for obtaining historical information on psychosocial and mental health events across a spectrum of disorders, (2) reveal unique patterns of an individual's life events in a manner not captured by standard clinical practice, and (3) illustrate individual and group historical information through an interactive graphical medium that could be readily examined by clinicians, patients, and family members. To accomplish these goals, we developed the Tulsa Life Chart (TLC), a structured assessment for graphically representing psychosocial historical data at individual and group levels. To test the feasibility and utility of this approach, we applied the TLC to the first 500 subjects of the Tulsa 1000 project, a longitudinal observational study of treatment-seeking individuals with mental health problems across the categories of major depressive disorder (MDD), anxiety disorders (ANX), eating disorders (ED), and substance use disorders (SUD) as well as those without mental health conditions [14]. We provide case examples with TLC graphical representations to illustrate the potential clinical utility of the TLC at the individual level. We hypothesized that the TLC would demonstrate feasibility and utility in detecting and displaying transdiagnostic differences in psychosocial trajectories across the life span. We also examined diagnostic group differences in trajectories of TLC psychosocial events over time to test specific hypotheses and to provide context from which individual case responses on the TLC could be examined. We hypothesized that all mental health conditions would be associated with more negative life events and stressors (eg, changes in residence, schools, and jobs) and fewer recreational activities relative to healthy comparisons (HCs). Given previous research suggesting that the negative effects of psychosocial stress accumulate over time [15], we hypothesized that these diagnostic group differences would be more apparent in later life periods. In addition, we hypothesized that SUD populations would report greater use of substances, starting in adolescence (consistent with previous research [16]), relative to all other diagnostic and HC groups.

Methods

Participants

The TLC was completed as part of the Tulsa 1000 project [14], which included participants aged 18 to 55 years, screened on the basis of several dimensional psychopathology scores: the Patient Health Questionnaire-9 (PHQ-9) [17] score greater than or equal to 10, Overall Anxiety Severity and Impairment Scale (OASIS) [18] score greater than or equal to 8, 10-item Drug Abuse Screening Test (DAST) [19] score greater than or equal to 3, and/or Eating Disorder Screen (SCOFF) [20] score greater than or equal to 2. These scales are commonly used screening questionnaires within research and clinical settings and were used within the Tulsa 1000 project to identify participants experiencing clinically significant symptoms of MDD, ANX, SUD, or ED. HC participants without elevations in symptoms or psychiatric diagnoses were also included. Participants were excluded if they (1) tested positive for drugs of abuse; (2) met criteria for psychotic, bipolar, or obsessive-compulsive disorders; (3) reported a history of moderate-to-severe traumatic brain injury, neurological disorders, or severe or unstable medical conditions; (4) had active suicidal intent or plan; or (5) reported a change in medication dose within 6 weeks of study enrollment. Full inclusion/exclusion criteria are described in the study by Victor et al [14]. These criteria were selected to minimize risks to participants and to address factors that may have confounded multilevel assessments conducted as part of the larger Tulsa 1000 study (including functional magnetic resonance imaging) while also optimizing generalizability to community mental health populations (eg, not excluding for many comorbidities or medication use). Participants were recruited from community mental health clinics and the general community through electronic and print advertisements. The Western Institutional Review Board approved the study. All participants provided written informed consent before completion of the study protocol and were compensated for participation. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008 (Trial Registration: ClinicalTrials.gov #NCT02450240).

This study focused on baseline data collected from the first 500 participants of the Tulsa 1000, for which longitudinal data collection is ongoing (recruited from January 5, 2015, to February 22, 2017; the study was conducted at the Laureate Institute for Brain Research, LIBR). TLC data were available for 499 individuals (see table in Multimedia Appendix 1 for the number of participants with data for each epoch). Participants were grouped by Diagnostic and Statistical Manual of Mental Disorders (DSM)–IV or DSM-5 diagnosis as determined by the Mini International Neuropsychiatric Inventory (MINI) [21], including MDD only, ANX only (social anxiety, generalized anxiety, panic, or posttraumatic stress disorder), comorbid MDD and ANX (MDD+ANX), SUDs (recreational drugs, excluding alcohol or nicotine; with or without comorbid ANX/MDD), EDs (with or without comorbid MDD, ANX, or SUDs), and HCs with no psychiatric diagnoses. Sample size, demographic information, and screening measure scores are shown in Multimedia Appendix 2.

Measures

Development of the TLC was informed by the general approach of the NIMH Life Chart [7,8] and by considering transdiagnostic psychosocial factors thought to contribute to mental health. The TLC was conducted as a structured interview by bachelor's- or master's-level research personnel and took approximately 2.5 hours to administer. Training in TLC administration was supervised by a board-certified psychiatrist (SK) and a licensed clinical psychologist (RA), with interviewers presenting each case as part of a weekly, supervised assessment review. In addition to the TLC, all participants completed screening measures and the MINI [21].

The TLC interview assessed birth date, location, and birth complications and then queried specific components from each of the following epochs: (1) birth to elementary school or age 5 years, (2) elementary school or ages 5 to 10 years, (3) middle school or ages 11 to 14 years, (4) high school or ages 15 to 18 years, (5) young adult or ages 18 to 25 years, and (6-8) for every 10 years thereafter to the age of the participant (ie, 25-35, 35-45, and 45-55 years). For each epoch, participants provided an average mood rating (1-10, with 1 being the worst they have ever felt and 10 being the best they have ever felt) as well as the frequency/number, start/end dates, and brief descriptions for each of the following: (1) places lived (residences); (2) schools attended (schools); (3) leisure activities (hobbies); (4) employment (jobs); (5) people they felt close to (people); (6) exposure or experiences with substances; (7) mental health treatments; (8) changes in family structure, for example, birth of a child, marriages, divorces, and so forth (change events); (9) negative (bad); (10) positive (good) events; and (11) any *other* events they felt were important. Participants were asked to rate their mood at the time of each negative, positive, change, and other events on the same 1 to 10 scale. For the TLC, we purposely used a mood rating that spanned positive affect (*best they have ever felt*) and negative affect (*worst they have ever felt*) such that the same scale could be used across different types of events (ie, rather than using measures of general distress). All data were entered electronically using Research Electronic Data Capture (REDCap [22]).

A 1-page electronic and interactive graphical representation was developed by exporting data using the redcap.js client module and creating interactive graphs using JavaScript along with the Google Visualization Application Programming Interface [23]. We provide 4 example TLCs, along with brief case summaries of each. For the purposes of confidentiality, information relating to identifiable patient characteristics and personal history has been modified, and each participant provided consent to use the presented information for publication. Interactive graphs for each case, REDCap forms, and code for creating the interactive graphs are available on GitHub [24].

To gauge user experiences of the TLC, a subset of 338 participants were asked to provide quantitative usability ratings, including the pleasantness of the interview, usefulness for better understanding their mental health, and how likely they would be to recommend the TLC to others. Open-ended questions were subsequently asked to gather qualitative feedback about the TLC. These questions included asking participants to elaborate on what was helpful and unhelpful and what they liked and disliked and to provide any other information they thought we should know about their experience. Interviewers made notes concerning the participants' responses, and thus, the comments are paraphrased rather than being verbatim responses from participants. The authors identified examples of positive and negative comments that were helpful in considering the potential utility of the TLC as well as potential improvements that could be made. Herein, we report the quantitative and qualitative user feedback obtained from participants. For the qualitative feedback, we provide illustrative excerpts highlighting participants' subjective experiences with the TLC concerning (1) insight into the trajectory of their mental health symptoms, (2) self-awareness of resiliency, (3) user feedback on the structure of the TLC interview, and (4) negative aspects of the TLC. We also provide a complete listing of all qualitative participant feedback obtained from participants.

Statistical Analysis

Quantitative analyses focused on evaluating (1) general mood ratings (*mood*), (2) the number of bad minus good events (*bad−good*), (3) the number of drug types exposed to (*substance use*), (4) the number of mental health treatments received (*treatment*), (5) the number of people they felt close to (*people*), and (6) the number of hobbies reported (*hobbies*). The number of residences was entered inconsistently by research personnel and was, therefore, not analyzed. We applied generalized linear mixed effects models (GLMMs) on each outcome measure using all available data from each epoch. Fixed effects included epoch, diagnostic group, age, and sex. The choice of distribution (eg, Poisson vs negative binomial for count data), whether to include epoch-by-group interaction effects, and method of capturing temporal dependency (random subject intercept or first-order autoregressive correlations) resulted in several combinations (see Multimedia Appendix 3). The optimal model was determined by the Akaike Information Criterion (AIC). Statistical analyses were conducted in R (version 3.5.0) [25] using the glmmTMB [26] package for GLMMs and the sjPlot [27] package for visualization of parameter estimates and conducting the likelihood ratio tests to test for significance of fixed effects. In addition to providing *P* values for significance testing, incidence rate ratios in log scale, that is, fixed effect coefficients from GLMM, were displayed to provide an indication of the magnitude of the effects identified. The R code used for analysis can be found through the Open Science Framework [28].

Results

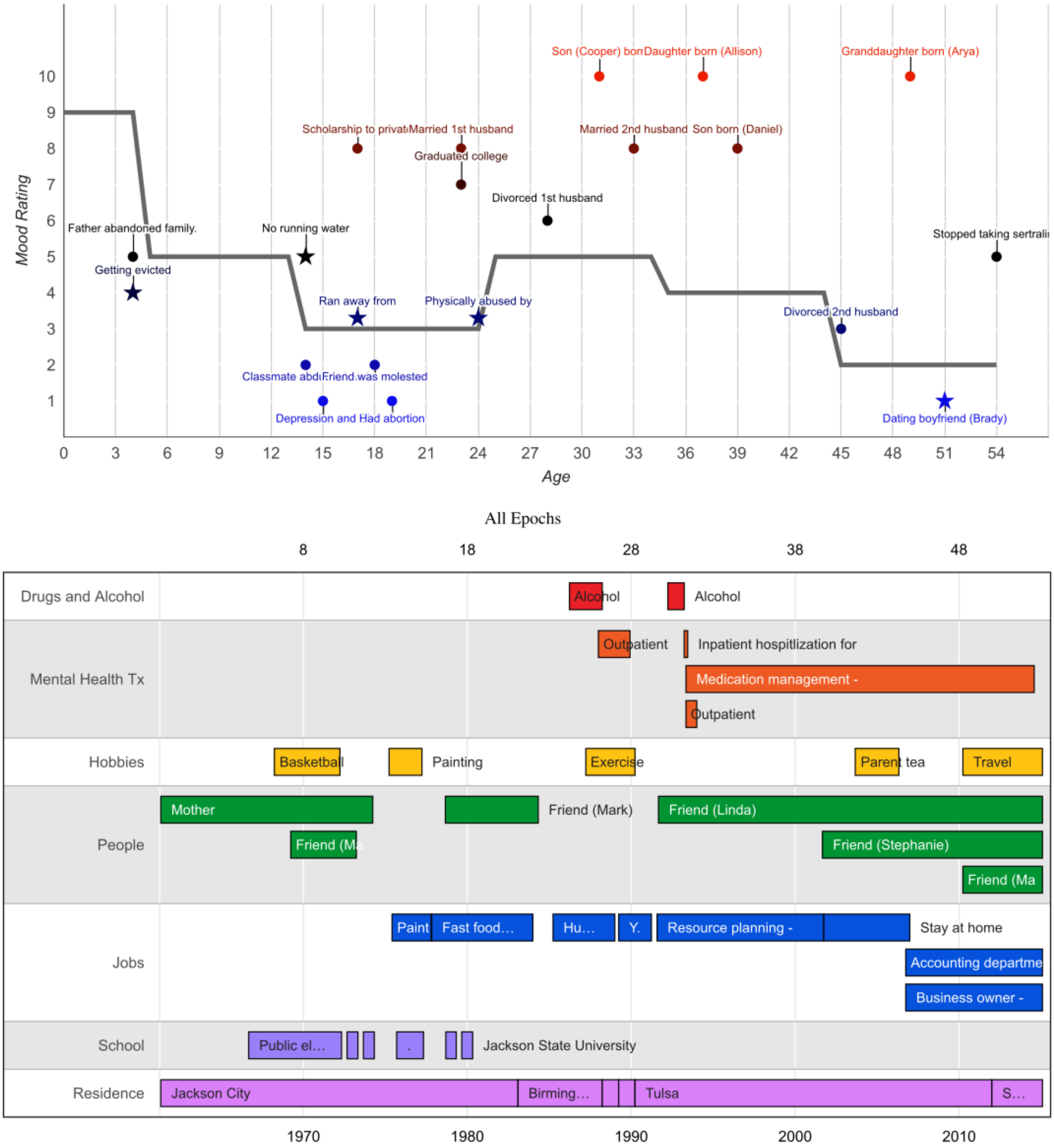
Individual Tulsa Life Chart Examples

Case 1 is included to illustrate the TLC at the individual level (Figure 1). Cases 2 to 4 are presented in Multimedia Appendix 4. Interactive TLCs for all 4 cases are available at [24]. In each graph, a top panel displays the average mood rating for each epoch (gray line). Positive, negative, change, and other events are plotted such that the vertical location represents the magnitude of the event-related mood rating, and the horizontal location represents the event date. In the interactive graphs, scrolling the cursor over each event displays additional details (eg, description, rating, and duration). A bottom panel displays information for each of the life components assessed (substance use, treatment, people, hobbies, jobs, schools, and residences), with the length of each box representing the event duration. A left-hand pane allows the user to selectively display/hide aspects of each graph. At the top of the page, a dropdown menu titled *Overall Graphs* displays individual case information alongside averaged group data, providing additional context for evaluation and interpretation.

Case 1 is a 54-year-old African American female. She was adopted at birth and raised by her adoptive parents in Jackson City, FL. At age 5 years, her adopted father reportedly took all the money out of their bank account and left. Her mother subsequently struggled financially and was evicted from multiple houses. She lived in a mobile home with no running water or electricity throughout high school. At age 14 years, a classmate was abducted and raped in an area near her school. It was about this age when she first began experiencing depression and suicidal thoughts. At age 17 years, she ran away from home and stayed with friends for about 1 month. She managed to obtain an academic scholarship to attend a private high school, and while there, she completed the requirements for her last 2 years in 1 year. She reported having an abortion at age 19 years. She indicated that she barely managed to obtain passing grades throughout college and graduated at age 23 years. Soon after, she married her first husband and began working as a human resources administrator. Her husband was physically abusive throughout their marriage. At age 25 years, she began drinking alcohol daily (1-2 glasses of wine). At age 28 years, she got divorced, quit her administrative job, and started working as a yoga instructor. Soon thereafter, she sought outpatient therapy for anxiety. At age 30 years, she moved to Tulsa, OK, and started working for a cellular phone company in the resource planning department. After experiencing sexual harassment from a supervisor, she resumed drinking alcohol daily (1-2 glasses of wine per night). At age 32 years, she was hospitalized in a psychiatric facility for 2 weeks after presenting to her local emergency department reporting suicidal ideation. During her inpatient stay, she was diagnosed with MDD and prescribed sertraline and bupropion. After discharge, she attended outpatient psychotherapy weekly for approximately 6 months and received medication management from a psychiatrist. At age 33 years, she married her second husband with whom she had 3 children. After her last son was born, she quit working to stay at home with her children. She divorced her second husband at age 45 years. Since then, she has worked in accounting at a hardware store and runs her own business. At age 51 years, she moved to Skiatook, OK, and met her current boyfriend, with whom she enjoys traveling. Six months ago, she stopped taking her sertraline and bupropion because of side effects ("feeling like a zombie"). Her anxiety and depression subsequently increased and continues to the present time.

As observed within the TLC graphs, case 1's mood decreased in childhood when her father left her family but continued to worsen into young adulthood and never completely recovered (despite engaging in treatment). She did not report many hobbies in her past but consistently obtained long-term employment at several places (each lasting >2 years). Although she did not report being close to many people in the past, she named 3 friends she currently feels close to. She has had very little exposure to drugs of abuse, with the exception of alcohol. Her scores on screening measures were as follows: SCOFF=1, PHQ-9=14, OASIS=11, and DAST=0, suggesting elevations in anxiety (severe) and depression (moderate) symptoms. Through the MINI, she was diagnosed with MDD, recurrent; generalized anxiety disorder; and panic disorder without agoraphobia.

Figure 1. Image from the interactive Tulsa Life Chart for Case 1, from the major depressive disorder comorbid with anxiety disorder diagnostic group.



Usability Ratings

Participants reported their experience completing the TLC as pleasant, on average (see Table 1). They also indicated that the TLC was somewhat helpful for better understanding their mental health and that they would be somewhat to moderately likely to recommend the TLC to others. Textbox 1 provides patient perspectives of the TLC, as illustrated through individual feedback comments provided by participants. All deidentified, qualitative participant feedback is provided in Multimedia Appendix 5.

Table 1. Average responses to the feedback questionnaire concerning the Tulsa Life Chart.

Question	Rating (scale 1-5)	
	Mean (SD)	Median
How was your experience of completing the life chart? (*Anchors: Very unpleasant, unpleasant, neutral, pleasant, very pleasant)*	3.73 (1.10)	4
How helpful was completing the life chart in better understanding your mental health? (*Anchors: Not at all, slightly, somewhat, moderately, extremely)*	3.07 (1.26)	3
How likely would you be to recommend the life chart to others with mental health concerns? (*Anchors: Not at all, slightly, somewhat, moderately, extremely)*	3.42 (0.85)	3

Textbox 1. Perspectives about the Tulsa Life Chart by individual participants.

As part of the Tulsa Life Chart (TLC) feedback questionnaire, 338 participants were asked to provide qualitative input concerning their experience with the interview. Below are paraphrased excerpts from these responses, organized by themes related to (1) the insight they experienced, (2) observations of resilience, (3) comments about the structure of the TLC, and (4) comments concerning potential negative aspects of the TLC.

Insight

- “The lifecharting allowed me to look at each event that has happened in my life and think about how it affected me. It gave me a base to work from in my therapy.”
- “It took one question to hash open my upbringing, and it made me think that if one question could open my mind that much then seeing a psychiatrist could be helpful. It makes it easier to heal when you can understand things, when you know the why behind something. Now I feel like I can move on easier and put things to rest.”
- “It helped me to recall certain life events and see a correlation between those events and my substance use, or thought patterns emerging that led to my substance use.”
- “[The lifechart] helped me understand my depression a lot more because I’ve never sat down and reviewed the different events in my life that may have contributed to it.”
- “I would like to keep up with this, maybe informally through a journal or documenting in some way.”

Resilience

- “Reflecting on all the memories that make up my life changed my perspective on why I’ve struggled with depression but also made me appreciate how resilient I have been in spite of those things.”
- “Lifecharting was helpful to realize how much I have conquered in my life and helped me understand how resilient I have been.”
- “I thought it was helpful to see how strong I was and how I overcame the bad things that happened.”

Structure

- “I enjoyed talking about both the ‘pros and cons’ of each life period and talking about both the good and bad.”
- “I liked the structure of the interview; having life broken down into each section made it easy to remember.”
- “I liked life charting because it lets you see your life through a window, it allowed me to do great reflection.”
- “Going through my life in a linear way puts things in a more organized perspective.”

Negative aspects

- “I did not like how long the interview was; the process was overwhelming at times.”
- “I wish I would have known ahead of time what the questions were.”
- “I felt frustrated when I wasn’t able to give precise dates.”
- “I did not like having to talk about the negative events that occurred throughout my life.”
- “I did not like having to share my story with a stranger.”

Group-Level Analysis

For GLMM analysis of mood ratings, the model selected by AIC identified epoch by diagnosis interactions (χ^2_{35}=118.0; P<.001). Specifically, MDD and MDD+ANX reported reduced mood ratings starting in elementary school, which became more pronounced in later epochs (Figure 2). ED also reported reduced mood ratings, but with the most robust decreases observed in high school years. For SUD, decreases in mood ratings did not occur until young adulthood. For bad-good events, the model selected by AIC also identified epoch by diagnostic group interactions (χ^2_{35}=339.0; P<.001; Figure 3). Specifically, ANX, MDD, and MDD+ANX exhibited greater bad-good event ratios compared with HCs, most robustly in later epochs (ie, the 35-45 years age range). The ED group exhibited the most bad-good events in middle and high school years. For SUD, the most bad-good events occurred during young adulthood and ages 25 to 35 years. For substance use exposure, the model selected by AIC indicated diagnosis (χ^2_5=210.0; P<.001) and epoch main effects (χ^2_7=1169.4; P<.001), characterized by the greatest level of substance use reported for all psychiatric groups (but most robustly for SUD) compared with HCs and for high school and young adult epochs (see Figure 4).

As shown in Multimedia Appendix 3, the models selected by the AIC for mental health treatment, social support, and hobbies indicated diagnosis and epoch main effects. Greater treatment seeking was observed for all psychiatric groups compared with HCs and for later epochs (Multimedia Appendix 3 and Figure 1). Less social support was observed for MDD, MDD+ANX, and SUD (but not ED) and for elementary through young adulthood (Multimedia Appendix 3 and Figure 2). Less number of hobbies were observed for MDD and SUD, and the greatest number of hobbies were reported for elementary to young adulthood (Multimedia Appendix 3 and Figure 3).

Figure 2. Average mood rating by epoch (left panel) and regression coefficients from generalized linear mixed effects models (right panel). Error bars on the left graph represent standard deviation; error bars on the right graph represent 95% CIs; positive values in orange, negative values in green), with P value thresholds noted with *.05, **.01, and ***.001. ANX: anxiety disorder; ED: eating disorder; HC: healthy comparison; MDD: major depressive disorder; MDD+ANX: major depressive disorder comorbid with anxiety disorder; SUD: substance use disorder.

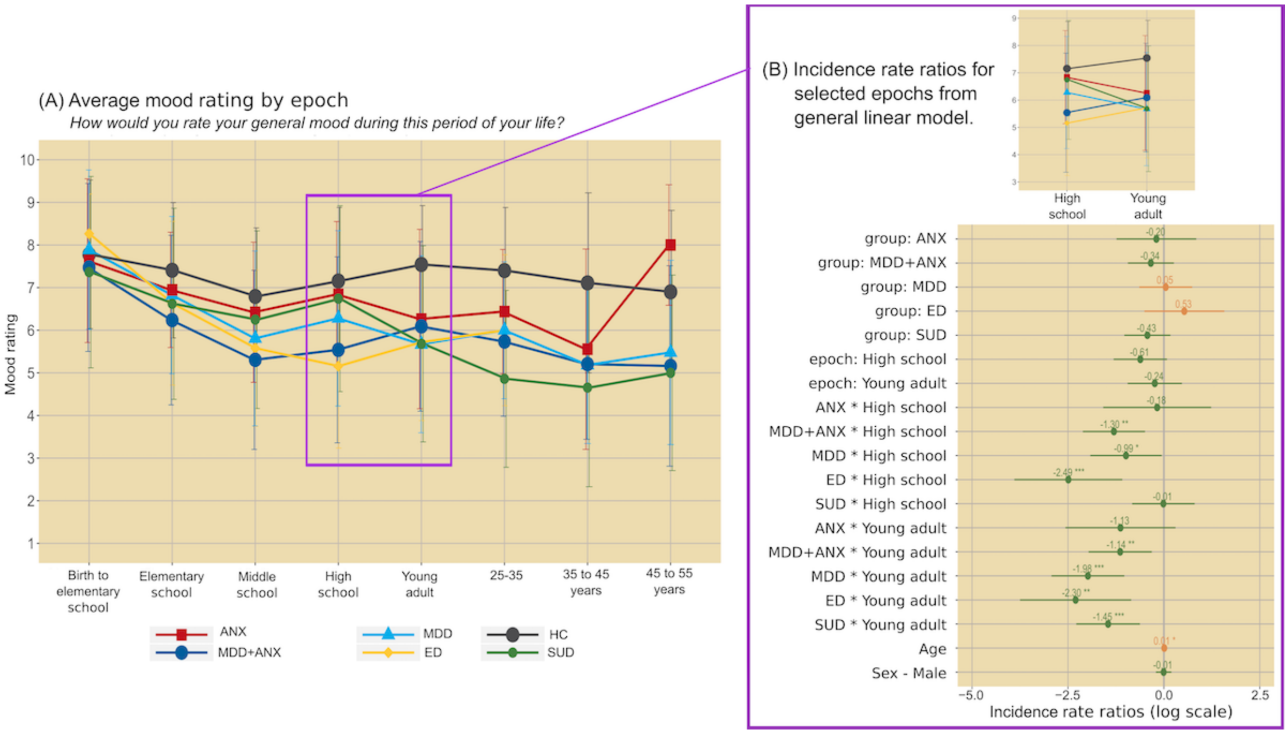


Figure 3. Average number of bad minus good events reported by epoch (left panel) and regression coefficients from generalized linear mixed effects models (right panel). Error bars on the left graph represent standard deviation; error bars on the right graph represent 95% CIs (positive values in orange; negative values in green) and *P* value thresholds noted with *.05, **.01, and ***.001. ANX: anxiety disorder; ED: eating disorder; HC: healthy comparison; MDD: major depressive disorder; MDD+ANX: major depressive disorder comorbid with anxiety disorder; SUD: substance use disorder.

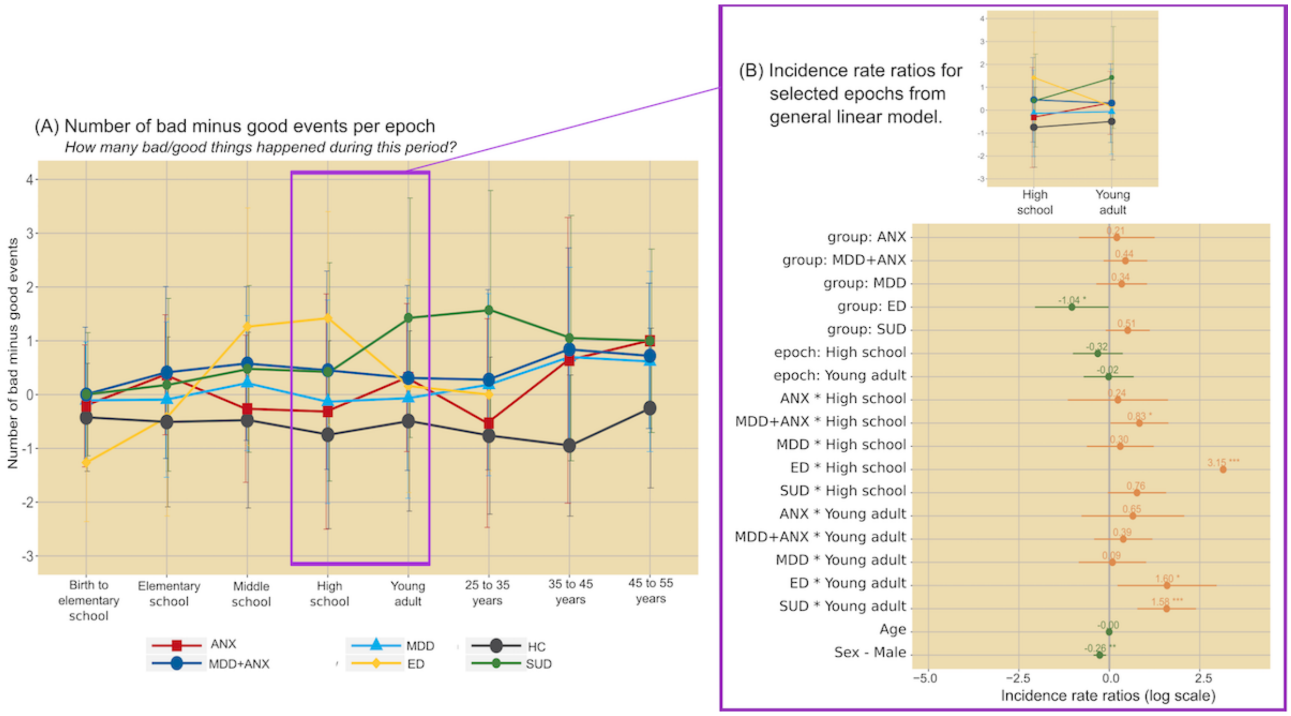
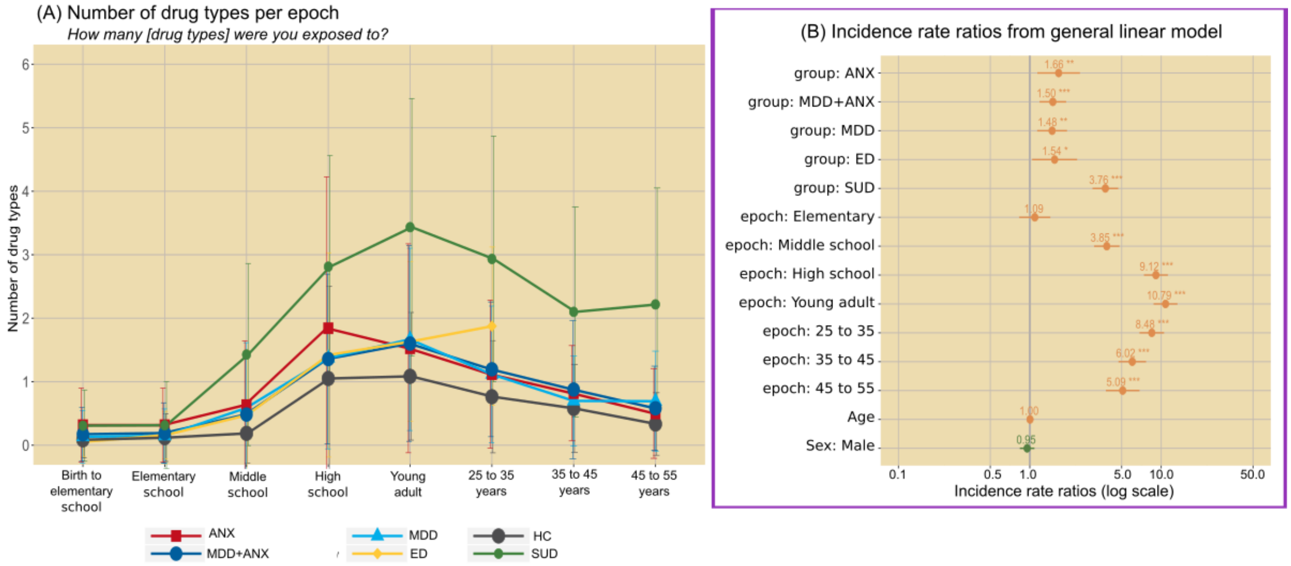


Figure 4. Average number of drug types exposed to by epoch (left panel) and regression coefficients from generalized linear mixed effects models (right panel). Error bars on the left graph represent standard deviation; error bars on the right graph represent 95% CIs (positive values in orange; negative values in green) and *P* value thresholds noted with *.05, **.01, and ***.001. ANX: anxiety disorder; ED: eating disorder; HC: healthy comparison; MDD: major depressive disorder; MDD+ANX: major depressive disorder comorbid with anxiety disorder; SUD: substance use disorder.



Discussion

Principal Findings

We developed the TLC as an electronic, structured method for assessing and longitudinally representing historical life events across the spectrum of depressive disorder, ANX, ED, and SUD, at individual and group levels, with the long-term goal of improving conceptualizations concerning the development, maintenance, and treatment of mental health by clinicians, patients, and family members. Within a large, transdiagnostic mental health sample, we used the TLC to identify how historical trajectories of psychosocial factors are influenced by life epoch and diagnosis, demonstrating the feasibility of the TLC through case examples, interactive TLC graphs, and patient feedback.

As illustrated in the cases provided, the TLC comprehensively communicates psychosocial information through a 1-page, Web-based graphical interface. For clinicians in practice settings affording limited face time with patients [29], the TLC could provide a quick, easily reviewable *fingerprint* of a patient's life, displaying in a single page the highs, lows, and major transitions. It also allows the viewer to modify what aspects of the TLC to view, depending on their needs, and to view the mood trajectory of 1 patient concurrently with the average of psychiatric comparison groups. The TLC could be useful for considering symptom onset and trajectory, thereby informing diagnosis and treatment selection, or facilitating deeper follow-up questions concerning the different domains assessed (eg, stability of early life, trauma history, and substance use). For psychologists or other licensed psychotherapy providers, the TLC could be integral for informing psychosocial interventions. For example, identifying hobbies individuals used to enjoy, positive events previously experienced, and sources of social support could be helpful for activity scheduling (eg, for behavioral activation therapy) [30]. As evidenced by participants' feedback, the TLC could provide therapeutic value in and of itself by enhancing self-awareness concerning links between life events, behaviors, and consequences, which could potentially improve motivation to engage with treatment. As self-monitoring is a cornerstone of most cognitive behavioral interventions, the TLC could provide a common platform from which to monitor mood fluctuations and associated events or behaviors. Given the Web-based platform, the TLC also represents a modifiable assessment instrument that could easily incorporate additional information to meet the individual needs of a clinician and patient (eg, to record cognitions, physical sensations, or other specific symptomatology).

By administering the TLC to a large, transdiagnostic mental health sample, we provided information concerning normative trajectories and potential differences in these trajectories by psychiatric diagnoses. In general, people in this study reported worse mood and more negative (vs positive) life events for later epochs, conflicting somewhat with previous work suggesting negative affect to peak around 20 to 40 years of age [31]. The number of hobbies and social support peaked from elementary through young adulthood and then exhibited a continuous decline. As expected, greater substance use was reported during young adulthood [16,32]. Numerous differences were also observed among the different psychiatric groups. These results support the plethora of research pointing to negative life events as precursors for mental health disorders [33,34] and the increased likelihood of substance use across mental health disorders [35,36]. Patients with MDD, MDD+ANX, and ANX reported increases in negative life events and decreased mood starting as early as elementary school, suggesting mood disturbances may often preexist the young adulthood age in which these disorders are usually diagnosed [16]. For SUD, decreased mood ratings were not observed until young adulthood, consistent with the most common age of onset [16]. Although all psychiatric groups (other than EDs) reported less social support, only MDD and SUD reported fewer hobbies than HCs. The decreases in leisure activities for MDD and SUD likely relate to changes in reward sensitivity and motivation that are hallmarks of these disorders [37,38]. Individuals with ED and ANX (with or without MDD) may retain motivation for such activities or even be motivated to engage in activities as a way of avoiding feared negative outcomes (eg, failure) [39].

Limitations and Future Directions

Given the potential positive benefits of the TLC endorsed by participants during the usability assessment, it is worth considering the pathway for feasible implementation and potential limitations and obstacles. The current version of the TLC was administered by bachelor's- or master's-level assessors and took 2 to 3 hours to complete. Although this is more cost-efficient than assessments requiring administration by licensed clinicians, it is still rather resource intensive. The duration of the interview, difficulty sharing personal details with the interviewer, and difficulty recalling events at the time of the interview were highlighted as potential negative aspects of the TLC by some participants. A self-administered version could optimize efficiency, help to facilitate broad adoption by clinicians, and potentially address some of these participant concerns. A recent empirical study of NIMH Life Chart data in individuals with bipolar disorder reported similar results regardless of clinician administration or self-administration, supporting the potential for such an approach [40]. To optimize access and continuity of care, the TLC could be hosted on a website for patients to complete on their own, with different clinicians given access as needed. However, this raises potential security and privacy concerns that would need to be addressed with information technology and informed consent methods. It should also be recognized that recall of past events and mood ratings could be influenced by recency effects, current mood, or other unknown factors [41,42]. Thus, the TLC may reflect a patient's perception of their life history, rather than a factual historical account. However, it is possible that after a patient has established a retrospective life chart, they could continually update the TLC prospectively as a momentary assessment tool [43], thus enhancing the reliability of information gathered and allowing for mutual evaluation of trajectories by patient and clinician over time.

The next steps in the development of the TLC are to improve the user experience of individual patients, to investigate the potential clinical utility of this tool from the health care provider perspective, and to enhance the potential for acceptability, scalability, and integration into health care settings by patients and providers. Over the short term, this will likely include (1) developing an interactive self-report version of the TLC that reduces completion time, reduces the personnel cost associated with administration, and increases the ability to deploy the TLC to different clinical settings; and (2) obtaining feedback from clinicians concerning the potential clinical utility of the TLC (eg, by asking them to provide the TLC to a subset of patients and assessing whether the information provided in the TLC improved their clinical understanding of the patient or improved their treatment delivery). In this context, clinicians could include providers across the health care spectrum, such as psychiatrists, psychologists, psychotherapists, primary care physicians, and health care extenders, including nurses, social workers, and medical assistants. Next steps over the long term include (1) identifying ways to link or embed the TLC within the electronic health records of health systems (eg, Epic and Cerner), which could enhance the clinical utility of the TLC for providers across the health care spectrum; and (2) exploring ways in which the TLC might be personalized toward life experiences, such as enabling the linking of nonmedical data with social media websites (eg, perhaps allowing for linking of important events to uploaded pictures, further facilitating the tracking of important life events).

Generalizability of Findings

In regard to the generalizability of these findings, the current sample consisted of individuals recruited from a community-based sample reporting clinically significant mental health symptoms related to ANX, depressive disorder, SUD, or ED, the latter of which was underrepresented. The sample was somewhat overrepresented in regard to white and Native American populations and underrepresented in regard to Hispanic and Latino, black and African American, and other minority populations, compared with the broader US population [44]. The average family income for the sample was relatively similar to national averages [45], but there were substantial differences in family income between participant groups (with the substance use group reporting the lowest levels of income overall). Future work is needed to establish whether these group-level findings provide meaningful comparison data for individuals with different racial or ethnic backgrounds, income levels, or symptom profiles.

Conclusions

Understanding a patient's life history is essential for informing their mental health diagnosis and treatment planning. Clinicians use historical interviews as a way to gather facts and information, to better understand the patient's trajectory of symptoms and experiences, and to build rapport by communicating that understanding back to patients [46]. The TLC described herein provides 1 strategy for combining the benefits of structured assessments with that of a more clinically oriented and personalized interview. Furthermore, the TLC allows for a 1-page graphical representation of an individual's life history, providing an efficient method for reviewing a multitude of other psychosocial factors often considered important in the development and treatment of psychiatric disorders. The TLC offers a life-charting method that is relevant across psychiatric conditions and has the potential for informing and enhancing diagnosis and treatment.

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Authors' Contributions

All designated authors meet all 4 criteria for authorship in accordance with the International Committee of Medical Journal Editors recommendations, including providing substantial contributions, drafting or revising the work for important intellectual content, providing final approval of the version for publication, and agreement to be accountable for all aspects of the work. RA contributed to the conception and design of the TLC, analytic plan, interpretation of data, and drafting and revising the work for publication. MP contributed to conception and design of the TLC, analytic plan, interpretation of data, and revising the work for publication. RK contributed to the acquisition, analysis, and interpretation of data and revising the work for publication. JT contributed to the acquisition, analysis, and interpretation of data; programming for the TLC interactive graphical displays; and revising the work for publication. TV contributed to the acquisition, analysis, and interpretation of data and revising the work for publication. HY contributed to the analysis and interpretation of data and revising the work for publication. SK contributed to the conception and design of the TLC, analytic plan, interpretation of data, and drafting and revising the work for publication. The T1000 investigators are the remaining investigators that substantially contributed to the Tulsa 1000 study, including the concept and design of the TLC, and provided revisions of the work for publication. The Tulsa 1000 Investigators include: Jerzy Bodurka, PhD; Justin Feinstein, PhD; Jonathan Savitz, PhD; Yoon-Hee Cha, MD, and Jennifer L Stewart, PhD

Conflicts of Interest

RA reports grants from the NIMH, the National Institute of General Medical Sciences, and the Oklahoma Science and Technology Research and Development. MP is an advisor to Spring Care, Inc, a behavioral health startup; he has received royalties for a paper about methamphetamine in UpToDate and also has received support from the National Institute of General Medical Sciences. MP, RK, JB, YC, HY, JF, and JS report receiving support from the National Institute of General Medical Sciences. JT and TV report no competing interests or outside support. JS received support from the NIMH and the National Institute of General Medical Sciences. SK reports grants from the NIMH, the National Institute of General Medical Sciences, and the Intra-Cellular Therapies Inc. The copyright for the TLC is owned by LIBR (Registration TXu002163895).

Multimedia Appendix 1
Number of participants with Tulsa Life Chart data from each epoch.

[DOCX File , 15 KB - mental_v7i1e16919_app1.docx]

Multimedia Appendix 2
Demographic information and symptom severity of study sample.
[DOCX File , 19 KB - mental_v7i1e16919_app2.docx]

Multimedia Appendix 3
Supplemental results from generalized linear mixed-effects models examining epoch and diagnostic effects on Tulsa Life Chart categories.
[DOCX File , 1344 KB - mental_v7i1e16919_app3.docx]

Multimedia Appendix 4
Supplemental examples of individual cases assessed using the Tulsa Life Chart.
[DOCX File , 1401 KB - mental_v7i1e16919_app4.docx]

Multimedia Appendix 5
Participant feedback concerning their experience completing the Tulsa Life Chart.
[XLS File (Microsoft Excel File), 139 KB - mental_v7i1e16919_app5.xls]

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Abbreviations

AIC: Akaike Information Criterion
ANX: anxiety disorder
DAST: Drug Abuse Screening Test
DSM: Diagnostic and Statistical Manual of Mental Disorders
ED: eating disorder
GLMM: generalized linear mixed effects models
HC: healthy comparisons
LIBR: Laureate Institute for Brain Research
MDD: major depressive disorder
MDD+ANX: comorbid major depressive disorder and anxiety disorders
MINI: Mini International Neuropsychiatric Inventory
NIMH: National Institute of Mental Health
OASIS: Overall Anxiety Severity and Impairment Scale
PHQ-9: Patient Health Questionnaire-9
REDCap: Research Electronic Data Capture
SUD: substance use disorder
TLC: Tulsa Life Chart

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Original Paper

Atypical Repetition in Daily Conversation on Different Days for Detecting Alzheimer Disease: Evaluation of Phone-Call Data From a Regular Monitoring Service

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Abstract

Background: Identifying signs of Alzheimer disease (AD) through longitudinal and passive monitoring techniques has become increasingly important. Previous studies have succeeded in quantifying language dysfunctions and identifying AD from speech data collected during neuropsychological tests. However, whether and how we can quantify language dysfunction in daily conversation remains unexplored.

Objective: The objective of this study was to explore the linguistic features that can be used for differentiating AD patients from daily conversations.

Methods: We analyzed daily conversational data of seniors with and without AD obtained from longitudinal follow-up in a regular monitoring service (from n=15 individuals including 2 AD patients at an average follow-up period of 16.1 months; 1032 conversational data items obtained during phone calls and approximately 221 person-hours). In addition to the standard linguistic features used in previous studies on connected speech data during neuropsychological tests, we extracted novel features related to atypical repetition of words and topics reported by previous observational and descriptive studies as one of the prominent characteristics in everyday conversations of AD patients.

Results: When we compared the discriminative power of AD, we found that atypical repetition in two conversations on different days outperformed other linguistic features used in previous studies on speech data during neuropsychological tests. It was also a better indicator than atypical repetition in single conversations as well as that in two conversations separated by a specific number of conversations.

Conclusions: Our results show how linguistic features related to atypical repetition across days could be used for detecting AD from daily conversations in a passive manner by taking advantage of longitudinal data.

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KEYWORDS

dementia; Alzheimer disease; speech analysis; screening; monitoring; behavioral marker; daily conversation

Introduction

As the world's elderly population increases, the number of people living with dementia is rising rapidly, making dementia an increasingly serious health and social problem. As of 2018, approximately 50 million people globally were living with dementia, corresponding to about 7.3% of the world's over 65-year-olds [1]. The total worldwide cost of dementia has risen significantly, being estimated to reach over US $1 trillion in 2018 [1]. At the same time, diagnostic coverage worldwide remains so low that only 40% to 50% of people with dementia have been diagnosed, even in high-income countries [2]. The low-diagnosis coverage makes it more difficult for many patients and their families to receive appropriate support and care. Taking this into consideration, health monitoring technology and services are expected to help increase the diagnosis coverage by detecting signs of cognitive decline resulting from dementia in everyday situations [3,4].

One of the clues for detecting cognitive decline resulting from Alzheimer disease (AD) in everyday situations can be obtained by identifying the evolution of a patient's language as their AD progresses. While the most typical symptom of dementia is memory impairment due to the medial temporal lobe shrinking [5,6], both retrospective analysis and prospective cohort studies have shown that language dysfunctions prevail even from the presymptomatic period [7,8]. Moreover, studies on pathologically proven AD patients showed that they exhibited syntactic simplification and impairment in lexical-semantic processing [9,10]. A growing body of studies on probable AD patients has also shown that many aspects of speech and language, including grammatical and informational content as well as acoustic characteristics such as the pitch contour, show deficits as AD progresses [4].

Previous computational studies attempted to measure these language dysfunctions in AD patients on the basis of such findings by using acoustic, prosodic, and linguistic features [10-34]. For example, the short-term memory loss attributed to dementia often makes normal conversation difficult due to language dysfunctions such as difficulties with word-finding and word-retrieving [35,36]. These language dysfunctions have been measured by tallying pronoun frequency and fillers, including nonwords and short phrases (eg, "umm" or "uh") [13,37,38]. The reduction in speech expressiveness is another language dysfunction typically observed in AD patients. This reduction is measured by the decrease in adjectives and indicators related to vocabulary richness [11,39]. Using a combination of these features, previous studies have succeeded in differentiating healthy controls and AD patients [22,37]. However, they mainly investigated speech data obtained while participants took part in neuropsychological tests such as verbal fluency, story recall, and picture description tasks [40]. Whether and how we can measure language dysfunctions resulting from AD during daily conversations remains largely uninvestigated. Because the conversational content and cognitive workload vary in daily conversations where people do not engage in specific tasks, we need to reinvestigate what kinds of speech features could be useful for identifying AD patients. In terms of the language dysfunctions of dementia patients in everyday conversations, previous observational and descriptive studies reported atypical repetition of words and topics as a prominent characteristic [41]. While this repetition has been typically reported to occur in the same conversation, it also appears in separate conversations that may be held on different days. Because it has not been objectively measured, investigating how word and topic repetition differs in AD patients is a promising first step.

In this study, we analyzed the conversational data of seniors with and without AD obtained from longitudinal follow-up in a regular monitoring service. We used natural language processing techniques to automatically measure atypical word and topic repetitions and then investigated whether and how characteristics in topic repetition differed between seniors with and without AD. The results indicated that both linguistic features related to word and topic repetition in paired conversations on different days had better discriminative powers compared with other linguistic features used in previous studies on connected speech data during neuropsychological tests. We also found that they peaked at a specific interval day (around seven days), not at a specific number of conversations. On the basis of these results, we demonstrate how quantifying atypical repetition in continuous and passive monitoring of daily conversations can help automatically detect AD.

Methods

Data and Participants

We used conversational data obtained during phone calls with a regular monitoring service for seniors provided by Cocolomi Co, Ltd (Figure 1A). In this service, communicators call and talk with older individuals once or twice a week, typically for 10 to 20 minutes of free conversation. All communicators received training and communicated with participants in accordance with the company guidelines for encouraging participants to speak. In this service, one communicator is typically assigned to a participant, and that participant talks with the same communicator. They manually transcribe the conversations in a spoken-word format by omitting incomplete words and fillers and forward the texts to family members such as their children. They used either home phones or smartphones. All conversations were conducted in Japanese. We analyzed these transcribed text data. All participants agreed to having their conversational data used for research purposes. This study was conducted under the approval of the ethical committee of Shizuoka University and performed in accordance with the Ethical Guidelines for Medical and Health Research Involving Human Subjects.

The data were obtained from 15 Japanese people (12 females and 3 males aged 61 to 91 years; mean 76.8 [SD 9.4] years). Of these, 2 females had received the diagnosis of AD. The morbidity information for other diseases was not available. The communicators knew the diagnosis status of the participants, but they communicated with them in accordance with the company guidelines and did not change conversation methods on the basis of the diagnosis status. The follow-up period ranged from 1 to 33 months (mean period 16.1 months). We analyzed data from 1032 phone calls in total, and the number of phone calls for each participant ranged from 4 to 226 (mean 68.8 phone calls). The average duration of a single phone call for each participant ranged from 6.8 to 22.2 minutes (mean time between participants 12.1 [SD 4.1] minutes). The total call time of our dataset was around 221 hours. Transcribed text data consists of only text spoken by participants, not communicators. The text data contained 1098 characters on average, and we analyzed 1,132,935 characters in total. Table 1 provides the overview of our dataset.

Figure 1. Atypical repetition in conversational data from regular monitoring service. A. Overview of regular monitoring service. The manually transcribed text of the conversation was analyzed in this study. B. Schematic illustrating the paired samples of conversations separated by t days and n phone calls to extract repetition features across different conversations. C. Repetition features of seniors with and without AD. Violin plot is used to visualize the distribution of the data and its probability density. On each side of the violin is a kernel density estimation to show the distribution shape of the data. The wider portion of the violin indicates the higher density and the narrow region represents relatively lower density. The grey box with the whiskers in the violin is the boxplot. The box denotes the 25th (Q1) and 75th (Q3) percentiles. The whiskers denote the upper and lower adjacent values that are the most extreme within Q3+1.5(Q3-Q1) and Q1-1.5(Q3-Q1), respectively. The white dot in the box represents median value. Significant differences are denoted with asterisks (*P<.001). D. AUC-ROC score of topic repetition feature with different T days.

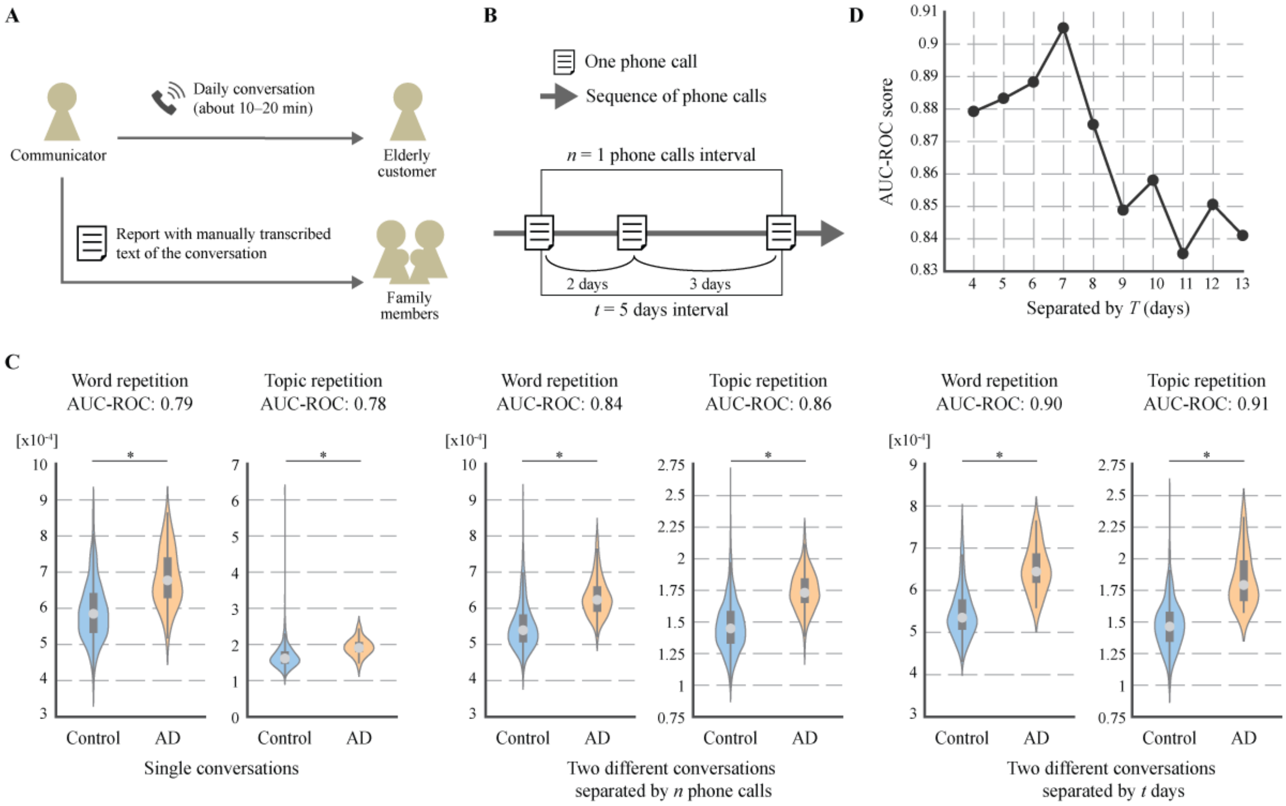

Table 1. Demographics of conversational data participants.

Status and gender	Age (years)	Duration (months)	Calls, n	Call time (min), mean (SD)	Number of characters, mean (SD)
Control					
F	61-62	11	31	7.8 (2.0)	422.7 (121.4)
F	63-64	14	32	14.0 (5.1)	1078.3 (369.8)
F	75-77	25	75	11.3 (8.5)	744.8 (215.5)
F	75-75	1	4	12.8 (3.1)	1365.0 (130.6)
F	78-78	9	64	10.3 (2.0)	815.2 (173.8)
F	79-80	6	23	11.7 (3.2)	1507.5 (457.4)
F	80-83	33	109	16.6 (4.7)	1499.7 (391.7)
F	82-83	19	72	6.8 (3.0)	811.2 (367.9)
F	88-89	17	104	11.2 (4.4)	944.5 (314.2)
F	91-91	9	35	22.2 (3.7)	2405.8 (433.2)
M	63-65	16	72	11.9 (3.1)	1146.8 (242.9)
M	67-70	33	132	10.6 (2.3)	999.4 (236.5)
M	82-85	30	226	17.7 (6.3)	1207.0 (497.7)
Alzheimer disease					
F	83-84	14	40	9.5 (2.8)	923.9 (409.2)
F	85-85	5	13	7.8 (1.8)	662.0 (199.1)
Mean (SD)	76.8 (9.4)	16.1 (10.2)	68.8 (57.2)	12.1 (4.1)	1098.0 (500.3)
Total	—	—	1032	13,230 (221 hours)	1,132,935

Extraction of Linguistic Features

From each item of phone call data, we extracted linguistic features related to word and topic repetition within single conversations, as well as the standard linguistic features used in previous studies to build models for AD screening from connected speech data during neuropsychological tests (for the list of features, please see the Standard Linguistic Features section) [10,14-34]. In addition, we extracted features related to word and topic repetition across different conversations from the text data of two phone calls separated by t days and n phone calls interval, respectively (Figure 1B). Specifically, we used all possible pairs of two phone call data items separated by t days ($T–M<t≤T+M$) for specific days interval and n phone calls ($N–M<n≤N+M$) for specific phone calls interval. Optimal parameters for T (4,5,…,13) and N (3,4,…,12) were selected by performing a grid search for each feature. In this study, we used M=3, T=10, and N=7 for word repetition, and T=7 and N=9 for topic repetition.

For preprocessing, we used the Japanese morphological analyzer MeCab [42] to perform word segmentation, part-of-speech tagging, and word lemmatization on the transcribed texts. Words tagged as numerals or symbols were excluded from the analysis. Predefined stop words were also eliminated.

Word and Topic Repetition Features

We measured word repetition by using the feature focusing on the number of distinct words being used in a target document. Specifically, the feature was calculated by the inverse number of Honoré’s statistic (HS) [43], defined as $HS=100\log V/(1–V_{uni}/U)$, where V is the total number of words, U is the total number of distinct word types, and V_{uni} is the number of total distinct word types used only once. For the feature related to word repetition across two text data of different conversations, we combined the data of both texts and then extracted the feature from it.

For the features related to topic repetition, we used a biterm topic model (BTM) [44]. While conventional topic models such as latent Dirichlet allocation have typically been used for estimating the latent topics of conversations [45], BTM was designed to extract latent topics from a limited amount of context, such as that found in tweets and news headlines [44]. Accordingly, we used BTM for estimating the topic in sentences and then extracted features related to topic repetition within conversations. Specifically, we first divided a text document into sentences by using punctuation marks. We then applied a BTM to a set of all the sentences, extracted word probability vectors for each K topic and obtained topic proportions allocated to each l sentence. For example, when a text document consisted of L sentences, we obtained $L–l+1$ vectors for topic proportions. We calculated pair-wise similarities with Euclidean distance and used the inverse number of the mean value as topic similarity features within single conversations. For the topic similarity features across two different items of text data D_i and D_j, we calculated pair-wise similarities between topic proportions in D_i and D_j and used the inverse number of the mean value. The parameters K=200 and l=3 were used.

We briefly describe how BTM works. In contrast to conventional topic models such as latent Dirichlet allocation [45], BTM directly models the generation of word co-occurrence patterns in the whole corpus to estimate topics from a small amount of context in a document [44]. The key concept is that if two words co-occur more frequently, they are more likely to belong to the same topic. The term *biterm* denotes an unordered word pair occurring in a short text. For example, a document with three distinct words generates three biterms:

$(w_1, w_2, w_3)\ \{(w_1, w_2), (w_2, w_3), (w_1, w_3)\}$.

In general, a document containing n distinct words generates $n\mathrm{C}_2$ biterms. The biterms are typically extracted from each sentence, and by combining them we get a corpus B for the target document as a set consisting of $\|B\|$ biterms. With the BTM, it is assumed that each topic is a multinomial distribution over the biterm (φ), and the whole corpus is a mixture of these topics (θ). The process of extracting biterms can be conducted as follows:

1. Draw a topic distribution θ ~ Dirichlet (α) for the whole corpus.
2. Draw a topic-specific word distribution φk Dirichlet (β) for each topic k.
3. For each biterm bi in the whole biterm set: Draw a topic assignment z ~ multinomial (θ). Draw two words wi,1, wi,2 ~ multinomial (φZi).

Following the above procedure, the probability of biterm $b_i=(w_{i,1}, w_{i,2})$ conditioned on the model parameters θ and α can be written as seen in Figure 2. For more details, we refer the reader to the original paper [44].

Figure 2. The equation of the probability of biterm bi.

$$p(b_i|\theta,\phi) = \sum_{K=1}^{K} p(z_i = k|\theta_k)\cdot\ p\left(w_{i,1}|z_i = k, \phi_{k,w_{i,1}}\right)\cdot p\left(w_{i,2}|z_i = k, \phi_{k,w_{i,2}}\right).$$

Standard Linguistic Features

On the basis of related work on connected speech data during neuropsychological tests, we extracted 29 linguistic features categorized into 4 types of linguistic features that would be useful for inferring AD: parts of speech, vocabulary richness, syntactic complexity, and perseveration [10,14-34]. Here, neuropsychological tests in previous studies include a picture description task using a picture of the Cookie Theft, comprehensive aphasia test, and the Wechsler Logical Memory tests [46-48].

The first feature set, related to parts of speech, consists of 14 features: frequency and the ratio of part-of-speech tags. We extracted the part-of-speech information by using Mecab [42] and then computed the frequency of occurrence of different parts of speech (nouns, verbs, adjectives, auxiliary verbs, and conjunctions). We also computed ratios, namely, each part of speech normalized by the total number of word tokens in the document. Analyzed part-of-speech tags included nouns, verbs, adjectives, pronouns, adverbs, auxiliary verbs, and conjunctions. We also calculated the ratio of noun to verb and the ratio of pronoun to noun.

The second feature set, related to vocabulary richness, consists of 3 features: type-token ratio (TTR), Brunét's index (BI), and HS [11,43]. This feature set measures lexical diversity, which tends to decrease in AD cases [11,13]. TTR compares the total distinct word types (U) to the total word count (V) as TTR=U/V. Using the same U and V, BI is defined as BI=$V^{U–0.165}$. Unlike other measures related to vocabulary richness, for this measure, the lexical richness becomes greater as BI becomes smaller. HS gives particular importance to unique vocabulary items used only once, also known as hapax legomena V_{uni}. HS is defined as HS=$100\log V/(1–V_{uni}/U)$.

The third feature set, related to syntactic complexity, consists of 7 features related to length metrics as well as dependency relations. For features related to length metrics, we calculated 4 measures consisting of mean length of sentences, total number of sentences in a document, total number of words in a document, and total number of characters in a document. For features related to dependency relations, we calculated total number of dependencies in a document, the average dependencies per sentence, and total dependency distance in a document. As for the dependency structures, we used CaboCha [49]. Dependency distance was calculated by the sum of all the linear distances between 2 syntactically related words in a sentence. This dependency distance has been considered an important index of memory burden and an indicator of syntactic difficulty [50].

The final feature set, related to perseveration, consists of 5 features. First, sentences were converted into term frequency–inverse document frequency (TF-IDF) vectors by using a bag-of-words model [51]. TF-IDF is a numerical statistic intended to reflect how important a word is to a document. By using TF-IDF vectors, we then calculated the cosine similarity between sentences [51]. We then calculated the proportion of sentence pairs equal to 0 and below 2 thresholds (0.3, 0.5) as well as the minimum and average cosine distances across all pairs of sentences.

Statistical Analysis

All statistical analyses were done in the R environment (R Foundation for Statistical Computing). A 2-tailed Student *t* test was applied for each feature to determine significant differences of enrichment between the two populations, and the resulting *P* values were adjusted with Bonferroni multiple testing correction. Adjusted *P* values below .01 were considered significantly different.

Results

We first investigated whether and how each of the 6 types of features for measuring repetition differed between seniors with and without AD: 2 repetition types (word and topic) × 3 data sources (single conversations, 2 different conversations separated by *t* days, and 2 different conversations separated by *n* phone calls). The discriminative power was measured by using both effect size (Cohen *d*) [52] and AUC-ROC. For Cohen *d*, an effect size of 0.80 is considered large, 0.50 is medium, and 0.20 is small [52]. ROC is a graphical plot that illustrates the diagnostic ability of a binary classifier system that ranges from 0 to 1.

Results showed that all 6 features had significant increased repetition in the AD group with large effect size (*P*<.001, 2-sided *t* test with Bonferroni multiple testing correction; Cohen *d* >0.80; Figure 1C). When we compared the discriminative power among them, the feature related to topic repetition across 2 conversations on different days showed the highest AUC scores and largest effect size (AUC=0.91); effect size of –1.76, 95% CI –2.15 to –1.36; Table 2). In addition, the features for word and topic repetition across different conversations separated by specific days interval and phone calls interval had larger effect size and higher AUC scores compared with those in single conversations (Table 2). We also found that the features extracted from conversational data at *t* days interval had better discriminative power than those at *n* phone calls interval (Table 2).

To deepen our understanding of the nature of repetition features across different days, we investigated the relationship between the discriminative power of the repetition features and interval days of paired conversations. Results showed that after they increased in the beginning, they peaked at around *T*=7 days and then had a tendency to decline (Figure 1D). This suggests that the difference of topic repetition between seniors with and without AD might change with a certain tendency, rather than randomly, with intervening days for two different conversations, and be the largest in the medium interval.

We next compared the repetition features with the standard linguistic features that were typically used in previous studies on connected speech data during neuropsychological tests [10,14-34]. Specifically, we extracted a total of 29 features used in previous studies: 14 features related to part-of-speech distribution, 3 features related to vocabulary richness, 7 features related to syntactic complexity, and 5 features related to perseveration. We found that 13 of the 29 features showed a significant difference between healthy control and AD groups in our dataset of daily conversations (*P*<.01, 2-sided *t* test with Bonferroni multiple testing correction; 11 out of 14 features relating to part-of-speech distribution, 1 out of 3 features relating to vocabulary richness, 1 out of 7 features relating to syntactic complexity, 0 out of 5 features related to perseveration; for exact *P* values see Multimedia Appendix 1). Through a comparison of discriminative power, we found that both topic and word repetition features across two conversations on different days outperformed all 29 features used in previous studies in terms of AUC-ROC scores (Table 2 and Multimedia Appendix 1), followed by conjunction ratio (AUC=0.89; effect size of –2.03, 95% CI –2.33 to –1.73) and pronoun to noun ratio (AUC=0.87; effect size of –1.94, 95% CI –2.24 to –1.64). These results indicate that topic and word repetition across daily conversations on different days might be a better indicator for differentiating AD than linguistic features used for inferring AD in neuropsychological test settings.

Finally, we investigated how changes in the language function of AD patients measured by linguistic features are different during neuropsychological tests and daily conversations. First, we summarized the linguistic features reported to be significant in distinguishing AD from healthy controls in previous studies on connected speech data during neuropsychological tests [10,14-34]. For the selection of the previous studies, we referred to the review article [40] as the baseline and added studies. Specifically, we considered only studies based on a group comparison with a group of healthy controls. Only studies focusing on connected speech through neuropsychological tests including picture descriptions have been considered. Semistructured or unstructured interviews including open-ended questions were not included. The features reported as significant in at least half of the studies were considered as the significant features. We then compared them with the results of statistical analysis on our dataset of free daily conversations.

This comparison showed that 19 out of 24 features showed a statistically consistent tendency with the results of the previous studies on connected speech data during neuropsychological tests (Table 3 and Multimedia Appendix 1). The other 5 features related to part-of-speech distribution (verb frequency, adjective ratio, and noun to verb ratio) and perseveration (average cosine distance and proportion of sentence pairs whose cosine distance is less than threshold 0.50) showed a statistically different tendency.

Table 2. Top 15 features of high discriminative power among linguistic features used in previous studies and repetition features. The table contains area under the receiver operating characteristic curve (AUC-ROC) score, effect size (Cohen d) with 95% CI, and *P* value of 2-sided t test with Bonferroni multiple testing correction.

Feature type	AUC-ROC[a]	Effect size (95% CI)	Adjusted *P* value
Topic repetition in two different conversations separated by *t* days interval (T=7)[b]	0.91	–1.76 (–2.15 to –1.36)	4.17E–17
Word repetition in two different conversations separated by *t* days interval (T=10)[b]	0.90	–1.67 (–2.06 to –1.29)	4.44E–17
Conjunction ratio	0.89	–2.03 (–2.33 to –1.73)	2.04E–41
Pronoun to noun ratio	0.87	–1.94 (–2.24 to –1.64)	3.17E–38
Topic repetition in two different conversations separated by *n* phone calls (N=9)[b]	0.86	–1.35 (–1.51 to –1.20)	2.75E–67
Noun ratio	0.86	1.38 (1.09 to 1.67)	4.28E–20
Word repetition in two different conversations separated by *n* phone calls (N=7)[b]	0.84	–1.22 (–1.36 to –1.08)	9.35E–66
Pronoun ratio	0.82	–1.50 (–1.79 to –1.21)	1.30E–23
Noun to verb ratio	0.81	0.63 (0.35 to 0.91)	2.73E–04
Honoré’s statistic	0.80	1.03 (0.75 to 1.32)	1.61E–11
Word repetition in single conversations[b]	0.79	–1.08 (–1.36 to –0.79)	1.57E–12
Topic repetition in single conversations[b]	0.78	–0.80 (–1.09 to –0.52)	7.62E–07
Conjunction frequency	0.77	–1.27 (–1.55 to –0.98)	4.22E–17
Noun frequency	0.75	0.71 (0.43 to 0.99)	1.66E–05
Adjective ratio	0.75	–1.06 (–1.34 to –0.77)	5.12E–12

[a] AUC-ROC: area under the receiver operating characteristic curve.

[b] Topic and word repetition features proposed by the authors.

Table 3. Comparison of the results of statistical analysis for the linguistic features between our study and previous studies. Our study analyzes speech data during daily conversations, while the previous studies analyzed connected speech data during neuropsychological tests. Sig and nonsig refer to significant and nonsignificant. For example, sig-nonsig in the inconsistent column indicates a feature that showed significant difference in the previous studies but not in our study. Cells contain the name of the corresponding features. Features whose statistical test results were not reported in the previous studies are excluded from this summary table. Information including *P* values of the statistical analysis in our study and the list of the previous studies is provided in Multimedia Appendix 1.

Feature category	Consistent (our study–previous studies)		Inconsistent (our study–previous study)	
	Sig-sig	Nonsig-nonsig	Sig-nonsig	Nonsig-sig
Part of speech (12)	• Noun frequency • Auxiliary verb frequency • Noun ratio • Verb ratio • Pronoun ratio • Auxiliary verb ratio • Conjunction ratio • Pronoun to noun ratio	• Adverb ratio	• Adjective ratio • Noun to verb ratio	• Verb frequency
Vocabulary richness (3)	• Honoré's statistic	• Type-token ratio • Brunét's index	—	—
Syntactic complexity (7)	• Mean length of sentence (utterance)	• Total no of words • No of sentences (utterances) • No of characters • Total dependency distance in a document • Avg dependency distance per sentence • Total no of distance in a document	—	—
Perseveration (2)	—	—	—	• Avg cosine distance • Cosine cutoff: 0.50

Discussion

Principal Findings

In response to the increasing demand for detecting dementia in everyday situations, we aimed to quantify language dysfunctions observed in AD from daily conversational data when the target is not performing neuropsychological or cognitive tasks. Although previous studies have succeeded in quantifying many aspects of language dysfunction, including grammatical and informational content as well as speech characteristics resulting from AD, they mainly investigated connected speech data collected while targets were engaged in neuropsychological and cognitive tasks; how language dysfunction in daily conversations can be quantified has not been sufficiently investigated. In this study, we focused on atypical repetition of words and topics reported by previous observational and descriptive studies as one of the prominent characteristics in everyday conversations of AD patients. Using conversational data of seniors with and without AD obtained from longitudinal follow-up in a regular monitoring service (from n=15 individuals including 2 AD patients at an average follow-up period of 16.1 months; 1032 conversational data items obtained during phone calls and approximately 221 person-hours), we investigated whether and how linguistic features related to word and topic repetition can be used for differentiating AD patients.

The results indicated that atypical repetition across different conversations could have a better discriminative power for AD compared to that within single conversations. We assume this atypical repetition across different conversations results from memory impairment that prevents speakers from remembering recent conversations. If so, the results suggest that the difference of memory performance between AD and healthy older adults might be larger after the lapse of some time than immediately, and linguistic features relating to atypical repetition could capture such difference even in daily conversations. In fact, deficits in episodic memory are one of the earliest detectable cognitive impairments in AD [53], and some experimental studies on episodic memory tasks such as word-list learning have reported that the forgetting rate passing from immediate to delayed recall in AD was significantly larger than that in age-matched controls [54]. These experimental studies seem to support our results. In addition, our results suggest that interval days between two conversations might be a more important parameter than the number of phone calls in terms of a discriminating power. These results might also be reasonable if the linguistic features relating to repetition can capture memory impairments resulting from pathological changes underlying AD. Furthermore, recent studies have reported accelerated long-term forgetting even in presymptomatic AD, which has garnered increased attention to detecting presymptomatic changes in AD [55]. From this perspective, our approach, which focuses on atypical repetition in daily conversations on different days, holds promise for detecting early signs of AD in everyday situations.

On the basis of comparisons with the standard linguistic features used in previous studies on connected speech data during neuropsychological tests, we found that features relating to atypical repetition in two conversations on different days had better AUC-ROC scores for differentiating AD than these linguistic features on speech data of daily conversations. The results suggest that repetition features across daily conversations on different days might be better indicators for detecting AD in everyday situations. We also compared the results of statistical analysis for each linguistic feature between previous studies on connected speech data during neuropsychological tests and our studies on daily conversations and found that about 80% of features (19 out of 24) showed a statistically consistent tendency. These results indicate that these linguistic features could be useful for inferring AD from speech data not only during neuropsychological tests but also during daily conversations. Features showing a statistically different tendency included those related to part-of-speech distributions and perseveration. In terms of the features of part-of-speech distribution, adjective ratio and noun to verb ratio showed significant difference between AD and controls in our study, while they were reported to have no significant difference in previous studies on connected speech data during neuropsychological tests [15,18,22,24]. In contrast, previous studies on speech data during semistructured interviews have reported that these two features were significant different [11,56]. Thus, language dysfunction in AD measured by these two features might be discriminative, especially in conversations in which the contents are less predetermined. As for the features related to perseveration, we found no significant difference in our dataset, while previous work reported the statistical significance of these features [22]. For example, one study used these features for measuring semantic similarity using a bag-of-words model in speech data during a picture description task and reported a significant difference between AD and controls [22,57]. Considering our results on the statistical analysis for these features, when we analyze unstructured and free conversational data such as daily conversations, language dysfunction in AD related to perseveration might need to be measured by combining a model for estimating the semantic topics (eg, BTM). In fact, the semantic similarity when using the BTM revealed a significant difference between AD and controls in our dataset.

In this study, we analyzed daily conversational data and showed that linguistic features, especially those related to repetition, can potentially be used for automatically detecting AD in a longitudinal and passive manner. Indeed, speech data collected in daily lives has gained increasing interest for clinical applications due to the improvement in audio quality recorded by portable devices and the expansion of voice-based interaction systems such as smartphones and smart speakers [4,58]. In particular, several studies that administrated cognitive and neuropsychological assessments over the phone have reported that speech features could be reliably extracted from phone recordings and used to build models for AD screening [59]. However, there are still relatively few studies on changes in speech features in daily conversations resulting from AD. Being capable of inferring AD from daily conversations would help with timely detection by frequent assessments with relatively short intervals, which might be difficult to do when using neuropsychological tests due to learning effects. From this perspective, we believe that the results of our study will help promote future efforts toward early detection of AD in everyday situations.

Limitations

Our work has several limitations. First, the number of participants was small, especially for AD patients, although the follow-up periods and number of conversations for each participant were relatively long and large. The results of a post hoc power analysis revealed that we would need at least two additional AD patients to obtain more than 0.80 of the power. A second limitation is the lack of information about AD severity and stage. We analyzed conversational data collected from the users of a regular monitoring service, and as such, were not able to obtain information related to clinical assessments, such as Mini-Mental State Exam scores and biomarkers (aside from AD diagnosis provided by medical doctors). Third, the age and gender of the control and AD groups were not matched. These three limitations stem from the fact that our dataset was collected from real users of an actual monitoring service. To clarify the relevance of our results obtained from the datasets with these limitations, we comprehensively compared the statistical results of each of the 24 linguistic features between our study and more than 20 previous studies and confirmed that our dataset showed a statistically consistent tendency with the previous studies. In addition to this perspective, because our dataset represents invaluable data collected from a real service and consists of 1032 conversational data items at an average follow-up period of 16.1 months, we believe our results can provide useful information for future studies toward the early detection of AD in the real world. The fourth limitation is the use of transcribed conversation data after omitting information related to incomplete words and fillers. While previous studies on connected speech during neuropsychological tests reported that these features did not significantly differ between controls and AD patients [40], we feel that further investigation is required, especially on speech data in daily conversations. The fifth limitation was the specific type of conversational data used. In this study, we analyzed free conversation between older adults and communicators mainly about the lives of the older individuals, but we need further research to confirm our results and extend the scope into various types of daily conversation, such as phone call conversations with their friends and face-to-face family conversations.

Conclusions

In summary, we investigated the daily conversational data of seniors with and without AD obtained from longitudinal follow-up in a regular monitoring service. We demonstrated that, while the linguistic features used in previous studies on connected speech data during neuropsychological tests can be used for detecting AD from daily conversations, the novel features related to repetition across conversations on different days could be a better indicator. We believe that our results can help to promote future efforts toward early detection of AD in everyday situations by taking advantage of speech data that can be collected in a passive, longitudinal manner.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Results of statistical analysis for the linguistic features in our dataset of daily conversations and the summary of the statistical analysis of these features in previous studies on speech data during neuropsychological tests.

[DOCX File , 38 KB - mental_v7i1e16790_app1.docx]

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Abbreviations

AD: Alzheimer disease
AUC-ROC: area under the receiver operating characteristic curve
BI: Brunét’s index
BTM: biterm topic model
HS: Honoré’s statistic
TF-IDF: term frequency–inverse document frequency
TTR: type-token ratio

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Original Paper

Smartphone and Internet Access and Utilization by People With Schizophrenia in South Australia: Quantitative Survey Study

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Abstract

Background: Web-based information and interventions for mental illness are increasingly being provided. There is an expectation that citizens have access to the internet and are competent in using technology. People with schizophrenia are often excluded from social engagement, have cognitive impairment, and have very limited income, all of which may reduce their use of technology.

Objective: This study aimed to investigate technology access, use of digital technology, and confidence in using technology among people with schizophrenia living in the community.

Methods: Face-to-face structured interviews with 50 people with schizophrenia (aged 18-65 years) living in the northern suburbs of Adelaide, South Australia, were conducted using an instrument designed to assess technology access and utilization.

Results: Most participants (42/50, 84%) owned a mobile phone, but only 58% (29/50) owned a smartphone. Two-thirds of participants (33/50, 66%) had access to the internet at home, using a smartphone or computer. Moreover, 40% (20/50) of participants used the internet at least daily, but 30% (15/50) of participants had never accessed the internet from any device. Approximately half of the participants (24/50, 48%) had never used Facebook. Participants rarely used community facilities (eg, libraries and cafes) to access the internet. There were no significant differences (*P* values ranged from .14 to .70) between younger participants (aged 18-34 years) and older participants (aged 35-64 years) in internet or smartphone access or confidence in using technology.

Conclusions: Although the sample size of this study is small, it shows limited technology access, use of digital technology, and confidence in using technology among the participants. This could be a barrier to the online delivery of information and interventions for people with schizophrenia. To better understand the impacts of such technological disadvantage and potential disparities in access and use of online resources, prospective studies should recruit a larger sample size and include control subjects matched for socioeconomic disadvantage.

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KEYWORDS

schizophrenia; schizoaffective disorder; internet; technology; computer; smartphone

Introduction

Background

Electronic mental (e-mental) health interventions are increasingly being implemented to assist in the management of psychiatric disorders and improve access to early intervention [1,2]. Those interventions apply information and communication technology, eg, computers and smartphones, to help promote mental well-being [1]. Although many of these interventions are aimed at high-prevalence mental health issues, eg, anxiety and depression [3], some specifically target people with psychotic disorders [4]. Emerging research suggests that engagement with cost-effective online interventions may be feasible for adults with a schizophrenia spectrum disorder [5]. For example, Alvarez-Jimenez et al [4] used an online platform to deliver clinical interventions to young people with early schizophrenia. Montes et al [6] found that the use of SMS text messages can improve antipsychotic medication adherence in people with schizophrenia, and studies by Ainsworth et al [7] and Ben-Zeev et al [8] demonstrated that smartphones could be beneficial in delivering interventions to patients with schizophrenia.

A systematic review by Alvarez-Jimenez et al [5] found that online, social media, and mobile phone–based interventions show promise in reducing the severity of positive symptoms and depression, reducing hospital admissions, improving social contacts, and enhancing medication adherence. There has been limited research on technology access (such as computers and smartphones), use of digital technology, and the level of confidence in using technology among individuals with schizophrenia. Access to technology is fundamental for the implementation of e-mental health.

In addition to potentially limiting access to e-mental health interventions, limited access to and use of technology could be associated with low levels of workforce engagement [9,10], reduced access to essential services (eg, government departments and financial institutions) [10] and transport systems [11], and limited access to social media [12]. Those factors could further impair social exclusion.

Miller et al [12] surveyed 80 inpatients and outpatients with schizophrenia at a university psychiatry service in the United States. They found that 56% of patients used text messaging, 48% had an email account, and 27% used social networking sites regularly. Gay et al [13] reported that of 457 people with schizophrenia, 24% used Web-based technology to help identify coping strategies, 42% listened to music to help block or manage voices, and 28% used technology to set alarms or reminders for medication management. However, Gay et al [13] used an online survey to collect this information; therefore, their sample was biased to those comfortable with online activities and did not include people who lacked internet access or competence using technology. A propensity weighting method was used to adjust for socioeconomic, attitudinal, and behavioral differences between people who respond to Web-based surveys and those who do not, but this appeared to be based on the general population rather than taking into account specific differences between those with schizophrenia and the rest of the community. Torous et al [14] reported substantial differences according to socioeconomic status. Only 33% of outpatients attending a state mental health clinic in the United States owned a smartphone and were willing to use it to monitor psychiatric symptoms, compared with 72% of those attending a private clinic [14]. Glick et al [15] surveyed 100 people with severe mental illness attending a public sector community mental health center in Atlanta, United States. They found that 85% of their participants had a cell phone and 37% had a smartphone, compared with 53% in a general population survey, and 44% of the socioeconomically disadvantaged people in the general community had smartphones. Both Torous et al [14] and Glick et al [15] surveyed outpatient populations that included a range of psychiatric diagnoses. In the study by Glick et al [15], 29.2% of people had schizophrenia or schizoaffective disorder, and Torous et al [14] did not include diagnostic information. Similarly, Ennis et al [9] drew participants from an early psychosis unit and from community mental health services in London. They did not give detailed diagnostic information. They found that technology use and access were similar to the general population. Collectively, those studies about the access to technology and the use of technology in patients with a schizophrenia spectrum disorder appeared inconclusive, which suggests a need for further investigation in those areas. Nonetheless, those findings correspond to the findings by Firth et al [16] who showed that smartphone app–based interventions for the whole population of patients with schizophrenia are not feasible when a significant portion of these people have no access to a smartphone. Together, those studies have justified the need to further investigate and understand their technology access and use, rather than implementing e-mental health interventions in the said population.

There are some specific aspects of schizophrenia that would be expected to be relevant in this study’s context. People with schizophrenia generally have some cognitive impairment [17], which would impact the ability to learn new skills using unfamiliar devices. Negative symptoms (eg, avolition and poor initiative), lack of social networks [18], and paranoid ideation [12] may also reduce engagement with technology. Furthermore, most people with psychotic disorders have very limited income [19]; hence, the purchase of smartphones and computers may not be possible. Libraries generally have computers with internet access that can be used by the general public, and internet access is available in many cafes, yet the usage of these low-cost options by people with schizophrenia is not known.

This study took place in the northern suburbs of Adelaide, a region with a low socioeconomic status. The official rate of unemployment is 7.7%, which is higher than that in other metropolitan areas in South Australia. Almost two-thirds (62%) of the population had not completed secondary school education [19], and in 2016, more than three-quarters (77%) of the northern population had received government benefits for more than 1 year [20]. The health status of people residing in this region is generally poorer than that of people residing in other regions in South Australia, with one-quarter of residents (25%) reported to have a serious or chronic health condition [21].

Objectives

The first objective of this study was to investigate technology access, use of digital technology, and confidence in using technology in people with schizophrenia living in a socioeconomically deprived urban region in Adelaide, Australia. The second objective was to compare internet usage, frequency of internet use, and confidence in using technology in younger and older adults with schizophrenia.

Methods

Recruitment

For this quantitative survey study, a member of the research team, psychiatrist (DL), identified stable outpatients with schizophrenia attending the Northern Adelaide Local Health Network (NALHN) community mental health center who were interested in participating in research. Afterward, another research team member (GW) recruited them for the study.

A total of 51 adults agreed to participate, but 1 of them was then found to have a diagnosis other than schizophrenia or schizoaffective disorder, resulting in the final sample of 50 adults. On participation, each participant was given an Aus $20 shopping gift card to reimburse their time. Owing to the budget allocated for this research project, only 50 adults with schizophrenia were recruited.

Participants and Exclusion Criteria

To ensure that participants had the capacity to consent for participation, individuals with a history of moderate/severe head injury, neurological disorders, or mental retardation (ie, IQ<70 as determined by the National Adult Reading Test [NART] [22]) were excluded.

Survey

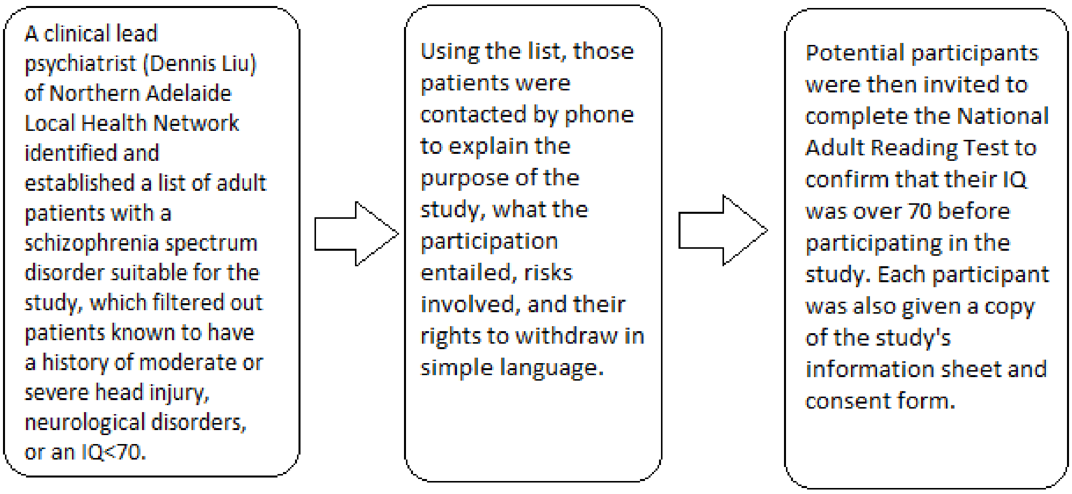
Two of the research team members (GW and CG, a psychiatrist) were responsible for the conceptualization and selection of this study's survey constructs, based on professional experiences in working with outpatients with schizophrenia. In addition to the NART, this study's interview consisted of Peters et al Delusions Inventory 21 [23], which measures delusion proneness. There were also items of demographic information and mental health history developed from a recent Australian study, People Living with Psychotic Illness 2010 [19]. Moreover, 80 individual technology-related questions that were used in this study were modified from surveys developed by Ennis et al [9], Muñoz-Neira et al [24], and Miller et al [12]. These questions assessed the following domains: (1) access, prevalence, and frequency of use of computers and mobile phones in general; (2) use of online resources (eg, banking, navigation, online shopping, email, social media, and well-being); and (3) attitudes to technology and self-rated competence.

For further details about this study's survey, please see Multimedia Appendix 1.

Procedure

The Human Research Ethics Committee of The Queen Elizabeth Hospital, Adelaide, South Australia, approved this research project. Before participation, GW explained to each participant the purpose of the study, what the participation entailed, the potential risks involved, and that they were free to withdraw without prejudice. Each participant was also given a copy of the study's participant information sheet and consent form. All participants gave written informed consent. The recruitment flowchart is shown in Figure 1. Individual interviews were conducted in the NALHN mental health sites, including a hospital-based clinical trials unit and a psychosocial rehabilitation and day program club, by a community rehabilitation worker (GW) under supervision. Instead of asking the study's participants to fill out the study questionnaire themselves, the primary researcher (GW) interviewed the participants as a means to gauge their understanding of the questionnaire questions. The interviews lasted for 45 to 60 min each.

Figure 1. Recruitment flow-chart for this study.



A clinical lead psychiatrist (Dennis Liu) of Northern Adelaide Local Health Network identified and established a list of adult patients with a schizophrenia spectrum disorder suitable for the study, which filtered out patients known to have a history of moderate or severe head injury, neurological disorders, or an IQ<70.

Using the list, those patients were contacted by phone to explain the purpose of the study, what the participation entailed, risks involved, and their rights to withdraw in simple language.

Potential participants were then invited to complete the National Adult Reading Test to confirm that their IQ was over 70 before participating in the study. Each participant was also given a copy of the study's information sheet and consent form.

Data Analysis

Chi-square tests were used to investigate whether younger participants (aged 18-34 years) had better technology access and more confidence in using technology than older participants (aged 35-64 years).

Results

Demographics

Participants were predominantly male with schizophrenia and were supported by government pensions. Moreover, 30% (15/50) of the participants were aged between 18 and 34 years, 30% (15/50) were aged between 35 and 44 years, and another 30% (15/50) were aged between 45 and 54 years. The remaining participants (5/50, 10%) were aged between 55 and 65 years (Table 1). In addition, 40% (20/50) of the participants had completed secondary school education; 52% (26/50) of the participants used Facebook, and their mean number of friends on Facebook was 52.86 (SD 114.58). Most participants (43/50, 86%) had been in contact with mental health services for 7 years or more, and 94% (47/50) of the participants took atypical antipsychotic medication.

Ownership of Devices and Usage

Overall, 42 participants (42/50, 84%) owned a mobile phone, but only 29 (29/50, 58%) owned a smartphone. In addition, 26 participants (26/50, 52%) owned a personal computer, and 14 participants (14/50, 28%) owned a tablet. Half of the participants owned more than 1 device. Table 2 shows the rates of use of technology, with 76% (38/50) using their devices at least weekly.

Regarding smartphone use, only 44% (22/50) of the participants had ever downloaded an app, and 38% (19/50) of the participants used GPS or navigated using maps; in contrast, the majority of the participants had used their device’s calendar (35/50, 70%), calculator (33/50, 66%), alarm (30/50, 60%), and camera (31/50, 62%). Only 32% (16/50) of the participants used their computers for more complex tasks such as word processing.

Table 1. Sociodemographic and clinical description of the sample (N=50).

Characteristics	Value
Gender, n (%)	
Male	31 (62)
Female	19 (38)
Age (years), n (%)	
18-34	15 (30)
35-44	15 (30)
45-54	15 (30)
55-65	5 (10)
Highest education completed, n (%)	
Did not complete year 9	3 (6)
Did not complete secondary school (year 12), no postsecondary school qualifications	25 (50)
Secondary school certificate	7 (14)
Postschool qualification (trade certificate or higher)	13 (26)
Unsure	1 (2)
Did not answer	1 (2)
Income (some had more than 1 source of income), n (%)	
Government pension	50 (100)
Full-time work	1 (2)
Part-time work	5 (10)
Casual work	2 (4)
Financial support from family	14 (28)
Financial support from other people	3 (6)
Diagnosis, n (%)	
Schizophrenia	43 (86)
Schizoaffective disorder	7 (14)
Duration of involvement with mental health services, n (%)	
1 to <3 years	1 (2)
3 to <5 years	1 (2)
5 to <7 years	5 (10)
≥7 years	43 (86)
Admitted to a mental health unit in the last 12 months	24 (48)
Medication, n (%)	
Typical antipsychotic medication	4 (8)
Atypical antipsychotic medication	47 (94)
Antidepressant medication	22 (44)
Antianxiety medication	2 (4)
Anticholinergic medication	2 (4)
Peters et al Delusions Inventory 21, mean (SD)	
Total score	70.26 (13.67)
Yes/no score	7.32 (4.55)
Distress score	20.18 (15.89)
Preoccupation score	20.40 (15.81)

Characteristics	Value
Conviction score	22.32 (16.24)
Intelligence score, mean (SD)	
Premorbid IQ (Wechsler Adult Intelligence Scale-Revised) score	103.06 (13.67)

Table 2. Access to technology (N=50).

Level of frequency	The use of any technology devices, n (%)	The use of internet, n (%)	Computer access at library or community center, n (%)	Wi-Fi access at library or cafe with smartphone, n (%)	Wi-Fi access at library or cafe with laptop, n (%)	The use of Facebook, n (%)	The use of email, n (%)	The use of internet banking, n (%)	Making online payments, n (%)	Engaging in self-development study activities online, n (%)	Looking and applying for jobs or studies online, n (%)	Frequency of using the internet to look up health-related information, n (%)
Never	9 (18)	15 (30)	34 (68)	43 (86)	48 (96)	24 (48)	19 (38)	28 (56)	33 (66)	35 (70)	33 (66)	27 (54)
Less than monthly	1 (2)	3 (6)	8 (16)	4 (8)	2 (4)	4 (8)	4 (8)	3 (6)	6 (12)	6 (12)	6 (12)	6 (12)
Monthly	0 (0)	3 (6)	5 (10)	2 (4)	0 (0)	4 (8)	6 (12)	3 (6)	4 (8)	4 (8)	3 (6)	11 (22)
Fortnightly	1 (2)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	2 (4)	0 (0)	0 (0)	0 (0)	0 (0)
Weekly	1 (2)	3 (6)	1 (2)	0 (0)	0 (0)	0 (0)	3 (6)	0 (0)	3 (6)	0 (0)	0 (0)	0 (0)
More than weekly	5 (10)	6 (12)	2 (4)	1 (2)	0 (0)	2 (4)	4 (8)	9 (18)	3 (6)	3 (6)	6 (12)	2 (4)
Daily	20 (40)	12 (24)	0 (0)	0 (0)	0 (0)	12 (24)	10 (20)	5 (10)	1 (2)	2 (4)	1 (2)	4 (8)
More than daily	13 (26)	8 (16)	0 (0)	0 (0)	0 (0)	4 (8)	4 (8)	0 (0)	0 (0)	0 (0)	1 (2)	0 (0)

Internet Access

Two-thirds (33/50, 66%) of the participants had access to the internet at home, using a smartphone, computer, or both. In addition, 40% (20/50) of the participants used the internet at least daily (Table 2). However, 30% (15/50) of the participants had never accessed the internet from any device. Community facilities, such as cafes, libraries, and community centers, which provide internet access, were rarely used for this purpose by the participants in this study.

Of the participants using the internet, 44% (22/50) used it for internet banking and 30% (15/50) to 34% (17/50) used it for online shopping, for making online payments, for applying for jobs or courses online, or for engaging with self-development activities. Only half of the participants with internet access used the internet for searching for local businesses (24/50, 48%) or to plan trips (25/50, 50%). Moreover, 54% (27/50) of the participants never used the internet to look up health-related information online, and 38% (19/50) of the participants reported that they could not find an Australian website about depression.

Digital Communication

Most participants (44/50, 88%) used mobile phones at least weekly to make and receive calls, with a lower proportion (32/50, 64%) using text messaging, and 38% (19/50) never used email. Social media was not routinely used, and 48% (24/50) and 90% (45/50) of the participants had never used Facebook and Twitter, respectively, on any device.

Attitudes to Technology

About 1 in 3 participants were not confident with using smartphone devices (Table 3). Fewer than half of the participants reported that they would have trouble with their day-to-day life if they did not have access to the internet (22/50, 44%), computer (22/50, 44%), or their smartphone devices (21/50, 42%).

A higher percentage of people aged 18 to 34 years used the internet at home (11/15, 73%), used the internet daily (7/15, 47%), and had greater confidence in using a computer or smartphone (60%) compared with people aged 35 to 64 years (22/35, 63%; 13/35, 37%; and 29% respectively). However, these differences between the 2 age groups were not statistically significant (Table 3).

Table 3. Internet usage, internet frequency, and confidence in using technology by age (N=50).

Internet usage, internet frequency, and confidence in using technology by age	18-34 years (n=15), n (%)	35-64 years (n=35), n (%)	Chi-square (*df*)	*P* value
Use internet on computer or mobile phone at home			0.2 (1)	.70
No	4 (27)	13 (37)		
Yes	11 (73)	22 (63)		
Frequency of internet use			2.4 (3)	.50
Never	3 (20)	12 (34)		
Monthly or less	1 (7)	5 (14)		
Weekly	4 (27)	5 (14)		
Fortnightly	0 (0)	0 (0)		
Daily	7 (47)	13 (37)		
Confidence in using computer			1.2 (2)	.56
Not at all confident	6 (40)	13 (37)		
Somewhat confident	3 (20)	12 (34)		
Confident or very confident	6 (40)	10 (29)		
Confidence in using smartphone			3.9 (3)	.14
Not at all confident	5 (33)	11 (31)		
Somewhat confident	1 (7)	11 (31)		
Confident or very confident	9 (60)	13 (37)		

Discussion

Principal Findings

Overall, technology access and engagement were lower in this study than in the rest of the Australian community. The prevalence of owning a computer (26/50, 52%) or smartphone (29/50, 58%) in our participants was lower than that in the Australian population (62% and 76%, respectively) [25]. Similarly, in 2016, it was estimated that 87% of Australians used the internet daily [26], compared with 40% (20/50) of our participants with schizophrenia, and 50% of Australians used social networking sites daily, compared with 32% (16/50) in our sample. Approximately 30% (15/50) of our sample had never accessed the internet.

Our results showed that most participants were only using certain device functions (eg, calling and SMS text messaging) and rarely used other functions of digital technology (eg, internet banking, social networking, self-development, health maintenance, and navigation). There was little use of e-mental health therapeutic interventions or psychoeducational sites.

Some studies provide smartphones to enable participants in research projects using e-mental health interventions. In contrast, participants in other research projects are required to use their own smartphone. Treisman et al [25] attributed the lack of engagement with technology by some people with schizophrenia to the cost of devices and lack of skills. Glick et al [15] argue that smartphones and internet plans are becoming affordable, but people with psychoses often describe living in poverty. In an Australian survey in 2010, 12% of the study sample reported having run out of food in the previous 12 months, and not having money to buy more [12]. In addition, it is possible that the costs associated with a technology device [27], a lack of knowledge about what device to buy, and how to set up internet access may be barriers to use. Furthermore, cognitive impairment is a core symptom of schizophrenia [28,29], so learning to use unfamiliar devices and to acquire technology skills could be challenging.

Increasingly, social engagement occurs via social media, and information from a wide variety of sources is provided online rather than using more traditional methods of communication. Many people with psychosis, including schizophrenia, experience social isolation [30,31], potentially with a lack of meaningful social participation. It appears that one-third of the participants would be unable to engage in social media. However, less than half of the participants showed that they would never struggle with their daily life if they had no access to the internet, computer, or their smartphone. Although the rationale was not investigated, such phenomena could be related to an adaptation to live without those technologies or the individual’s regular psychosocial rehabilitation support, which may include side-by-side assistance for activities of daily living offered by mental health support workers and clinicians, reducing the need to use technologies independently.

This study provides data on the level of access to digital technology and the self-reported confidence among adults with schizophrenia living in a socioeconomically deprived urban region in Australia. These findings may have implications for the design and scope of delivery of e-mental health interventions for this particular population, especially when there are e-mental health interventions that target psychoeducation (via the internet) and medication adherence (via SMS text messages) [32]. Yet, using e-mental health interventions requires a certain level of technology access, use, and confidence. When patients with schizophrenia do not use digital technology or lack the confidence to use it, they may not be able to fully use those e-mental health interventions.

Future Directions

Prospective studies may need to address barriers that prevent greater engagement with technology in this population, including paranoia [12], mistrust of devices, and access to the internet. Further research could also examine the barriers to accessing the internet in public areas (eg, public libraries), given that these resources were rarely used. Needless to mention that, in the NALHN's service catchment area, at least three libraries with free internet access and training are located within walking distances to the corresponding major shopping centers and supermarkets. This is particularly concerning, as the cost of purchasing devices and maintaining internet access may simply be too expensive for many people with schizophrenia, and these free services may be a useful means of access. Specific familiarization programs are needed to help with awareness of these facilities and with feeling welcome when attending. Ultimately, improved access and encouraging patients with schizophrenia to learn how to use technology may promote a greater range of technology uses, potentially including therapeutic interventions.

Limitations

The small sample size of this study limits generalizability. In addition, instead of assessing real-time usage and skills as a technology literacy assessment, this study relied on self-reported frequency of technology usage. This study did not assess technology literacy. In other words, this study did not capture the extent to which participants could carry out a task, eg, asking them to navigate a website, perform a search, and note any difficulties they encounter. Nonetheless, this research has tapped into the participants' confidence level regarding technology use. Future research could also include an economically and demographically matched healthy control group to more thoroughly examine factors unique to individuals with schizophrenia.

Conclusions

In conclusion, digital technology use and internet access were limited in this population. This may be addressed via the delivery of training to increase individuals' confidence in the use of technology. This training may be required before the online delivery of e-mental health interventions can be widely used in people with schizophrenia. Further research should examine the extent to which paranoia, cognitive deficits, and poverty limit people with schizophrenia from engaging with e-mental health interventions, smartphones, and computers to improve their mental health.

Authors' Contributions

All authors contributed to the manuscript and revised and approved the final draft.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Demographic information.
[DOCX File , 28 KB - mental_v7i1e11551_app1.docx]

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Abbreviations

e-mental: electronic mental
NALHN: Northern Adelaide Local Health Network
NART: National Adult Reading Test

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Original Paper

Assessing the Usability, Appeal, and Impact of a Web-Based Training for Adults Responding to Concerning Posts on Social Media: Pilot Suicide Prevention Study

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Abstract

Background: Suicide prevention remains challenging among youth, as many do not disclose suicidal ideation. Nearly one-third of American Indian and Alaska Native (AI and AN, tribal, or native) youth see concerning messages on social media at least weekly.

Objective: To prepare adults to support AI and AN youth who post or view concerning messages, our team designed an hour-long training: Responding to Concerning Posts on Social Media. This study tested the usability, appeal, and impact of the training.

Methods: A purposive sample of 70 adults was recruited to participate in the pilot, which included 2 study arms. Arm 1 participants completed a 30-min training video and reviewed accompanying handouts, including the Viewer Care Plan (VCP). The VCP provided a 3-step planning and response tool: (1) Start the Conversation, (2) Listen, Gather Information, and Assess Viewer Experience, and (3) Plan and Act. The intent of the VCP was to support and connect AI and AN youth who either view or post concerning messages on social media to life-saving resources. Those enrolled in arm 2 participated in an additional interactive role-play scenario with a coach that took place after the training, via text message. Participants provided qualitative and quantitative feedback on the training's relevance, appeal, and utility. Paired *t* tests were used to assess confidence in addressing concerning posts between pre- and postsurveys. Content analysis of the role-play transcripts was used to assess the quality and completion of the coached role-plays, in relation to the recommended VCP.

Results: Altogether, 35 participants finished the training and completed pre- and postsurveys; 22 participants completed the 6-month follow-up survey. Pre-post analyses of differences in means found significant improvement across several efficacy measures, including confidence starting a conversation about social media (P=.003), confidence contacting the person who posted something concerning (P<.001), and confidence recommending support services to youth who view (P=.001) or youth who post concerning messages (P<.001). Similarly, pre- to 6-month analyses found significant positive improvement across multiple measures, including confidence contacting the youth who posted (P<.001), confidence starting a conversation about social media with youth (P=.003), and an increase in the number of experiences recommending resources for youth who viewed concerning social media posts (P=.02). Of the 3 steps of the VCP, the least followed step in coached role-plays was sharing tools and resources, which is a part of the third Plan and Act step.

Conclusions: Findings indicate that the Responding to Concerning Posts on Social Media training is a promising tool to prepare adults to intervene and complete the VCP. Additional evaluation with a larger cohort of participants is needed to determine the unique impact of the role-play scenario and changes in mental health referral rates, behaviors, and skills.

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KEYWORDS

community health education; mental health; social networking

Introduction

Background

According to the Center for Native American Youth, suicide prevention remains one of the most daunting challenges for American Indian and Alaska Native (AI and AN, tribal, or native) communities [1]. Among Native youth in 9th to 12th grades, including teens aged 14-18 years, the past year prevalence of suicidal thoughts, suicide planning, and attempted suicide was nearly 15% in 2017 [2]. Consequently, suicide is the second leading cause of death for AI and AN youths aged 10-24 years, a rate that is 2.5 times higher than the national average [3]. Culturally relevant interventions are critically needed to stem the devastating, reverberating impact that adolescent suicide has on tribal communities and their families [4].

Emerging research has found that some at-risk youth disclose depression symptoms and suicidal ideation on social media channels, including Facebook, Twitter, and Instagram [5]. In a review of college-age social media profiles, 25% displayed references to depression symptoms on their Facebook page [6]. Similarly, in a 1-week period, over 200,000 publicly available tweets included the hashtag “depression,” and approximately 3% of the tweets referenced suicidality [7]. Not only are such references common, they can also be linked to real-life experiences. In one study, participants who displayed references to depression on Facebook also self-reported depression symptoms [8]. Lay media reports and scholarly papers have described tragic cases in which youths’ social media posts have indicated suicidality before attempting or dying by suicide [9]. These public social media disclosures provide new opportunities to identify AI and AN youth (aged 10-24 years) at risk and connect them to appropriate resources and support.

Social media is used frequently by the majority of AI and AN youth (aged 10-24 years) [10]. In a national survey of over 675 AI and AN teens and young adults in 2016, nearly 30% reported seeing concerning posts on a daily basis [10]. Further, multiple previous studies have suggested that teens and young adults from many communities, including AI and AN, are both able to identify social media posts suggesting mental health issues and willing to help intervene [11-14]. Some evidence suggests that AI and AN youth commonly respond when they see a concerning post. According to one survey of AI and AN youth, among those reporting that they saw a concerning post on social media, half indicated they had private messaged the person, 25% commented words of encouragement, one-third talked to the person offline, 20% did *nothing*, 12% *liked* or shared the message, and only 10% sought help from a trusted adult [10]. It is important to note that, although willing, AI and AN youth have indicated a lack of confidence in responding to concerning posts seen on social media [11-14]. There is a need to identify intervention partners to assist youth who observe this kind of content.

Social media connections between youth and adults, such as college students, are increasingly common [15,16], and previous research suggests approaches by which adults may conduct conversations related to sensitive or concerning social media posts. When it comes to discussion of posts seen on their own profiles, teens and young adults in college have reported willingness to discuss these posts, while indicating preferences about who conducts the conversation and how [17]. These preferences include having the conversation with someone the youth knows and that the conversational style be direct and open. Furthermore, teens and young adults in college express willingness to discuss concerning posts seen in electronic media such as email [18]. These findings support the inclusion of known, trusted adults in conversations to assist youth who have seen concerning social media posts. Tribal health educators, who are educators that work in a tribal or urban setting with tribal youth, may be ideally positioned to provide such assistance.

Objective

Despite the frequency of such concerning posts on social media and the willingness of youth to discuss this content with a known adult, formative research with tribal health educators across the United States found that less than 5% felt adequately prepared to address concerning social media posts [11]. This gap inspired the development of a 1-hour training intervention for adults who work with Native youth: *Responding to Concerning Posts on Social Media*. The aim of this pilot study was to determine the usability, appeal, and impact of the training on adult participants, while identifying components of the training amenable to improvement.

Methods

Training Intervention

The three primary learning objectives for the training were to prepare adults who work with Native youth to (1) identify youth who witness concerning social media posts, letting them know they need not respond alone, (2) assess those who see concerning posts and address their concerns, frustration, or fatigue, and (3) confidently implement the *Viewer Care Plan*, a multistep guide for educators to support youth who view or post concerning messages. These objectives were selected after conducting focus groups with 32 AI and AN youths in the Pacific Northwest of the United States, which identified common themes when responding to concerning social media posts: (1) youth frequently responded to concerning posts alone, (2) youth reported complicated barriers to intervening, and (3) youth identified resources and trusted adults they would like to reach out to for additional support [11].

The *Responding to Concerning Posts on Social Media* training intervention included four components: (1) a webinar, (2) a video, (3) handouts, and (4) a coached role-play scenario.

Web-Based Training

The Web-based training session was created using Articulate 360 software by Articulate Global, a comprehensive e-learning platform that allows for the creation of responsive and interactive Web-based trainings. The 1-hour Web-based training engaged participants through a self-paced training addressing the three learning objectives. The video included voiced-over narration through slides, which was also available as a readable transcript. The Web-based training session included 9 modules: (1) Welcome, (2) What are concerning posts? (3) Who is this training for? (4) Training goals and overview, (5) 30-minute video training, (6) Training handouts, (7) Community awareness activities, (8) Final review, and (9) A reminder for self-care.

Interactive slides were embedded throughout the Web-based training session to provide opportunities for reflection. The training was self-paced and could be advanced by clicking the *next* or *previous* buttons. A dropdown menu allowed participants to access any part of the training at any point, making access to specific content available for repeated review without needing to start over, and a resource tab gave participants access to downloadable handouts and resources.

Participants were instructed that, under the *supporting materials* tab on the Healthy Native Youth website [19], they could download two activity guides (one for adults and one for youth), which could be used to increase community awareness about concerning posts on social media. The Web-based training session concluded with a reminder for participants to take care of themselves, encouraging them to talk with a trusted friend or family member or a local mental health professional if needed and provided contact information for a clinical psychologist involved with the study.

Video

Midway through the Web-based training session, participants viewed a 30-minute video. The video provided an overview of why concerning posts should be taken seriously and shared findings from focus groups with Native youth about their experience seeing and responding to concerning posts on social media. The video included interviews with a Native family, who is from an AI background, and lost a child by suicide. In addition, the video included interviews with mental health professionals, who shared tips and examples for how to support youth and the community.

The video introduced the *Viewer Care Plan* (VCP), a three-step planning and response tool that could be referenced by participants to support youth in their community. The steps of this tool are summarized as follows:

- Step 1 - Start the Conversation: Normalize the topic at community gatherings and school events to raise awareness about concerning posts on social media. Let youth know they can come to you for help, as a trusted adult.
- Step 2 - Listen, Gather Information, and Assess Viewer Experience: If a youth approaches you, praise their efforts to help and assess their well-being. Let them know it can be scary or frustrating to repeatedly see concerning messages. Then, gather information from the viewer. What have they already tried? Who posted the message? How well do you know them? Do you know any trusted adults for the youth who posted the message?
- Step 3 - Plan and Act: Reassure the youth that you will take it from here. If you are comfortable contacting the person who posted the concerning message, use the question, persuade, refer (Question, Persuade, and Refer [QPR]) suicide intervention model. If you would prefer not to, contact another trusted adult to create an appropriate response plan.

The video stressed the importance of adults identifying themselves as trusted adults in the community whom youth can ask for help from.

Handouts

The Web-based training session concluded with an overview of the training handouts. These included a two-page summary of concerning posts, examples of concerning messages provided by youth during focus groups, and tips for talking about suicidality; a one-page VCP flyer and tip card; a QPR Institute training flyer to encourage folks to seek additional suicide prevention training; Kognito Web-based role-play simulations to prepare individuals to lead real-life conversations that change lives (free to tribes); a #WeAreConnected suicide prevention rack card; a bullying prevention brochure; and a cyberbullying prevention brochure.

Coached Role-Play

After completing the Web-based training session, a subset of participants was invited to participate in a coached role-play scenario. The goal of the role-play was to test and improve participants' skills as they implemented steps in the VCP. During the role-play, the research team played the part of a youth who had seen a concerning social media post and was reaching out to the participant as a trusted adult for help responding to the post. If the participant forgot or skipped steps during the interaction, the research team offered prompts related to important skills in the VCP (Table 1).

At the end of the interaction, participants were emailed a 3-minute video clip of an exemplar role-play scenario, modeling complete, successful use of the VCP.

Table 1. Ideal responses and coaching prompts provided during the role-play scenario.

Viewer care plan skill	Ideal response	Coaching prompt
Listen carefully and offer reassurance: Ask youth about the concerning social media post(s). Acknowledge that it can be scary, stressful, and frustrating. If relevant, discuss responder fatigue.	• Hi I'm so glad you're reaching out. Thank you, you are so brave. • It can be difficult to know what to do with concerning posts. It's great that you noticed and reached out to me.	• I'm feeling pretty scared and confused. I'm not sure if I should just ignore it, or what. What if they do something, then I'd feel awful. • Honestly, this is freaking me out. I want to say something, but just don't know what.
Gather information: What have you already tried? Acknowledge their attempts to provide support.	• Have you said or done anything yet in response to the post? • Did you like it? Share it? Message them? • Have you seen this person posting like this behavior? Is this common for them?	• I direct messaged them like 5 times, texted 'em, and they continue to post depressing stuff • I'm over it, I think I'm just going to delete them from my FB. • I tried reporting it to Facebook, but it didn't seem like they did anything-it's stressing me out. • I don't know who to trust, so I haven't told anybody.
Ask about your relationship to the person posting concerning content: Are they a close friend? Acquaintance? Family member? Avoid interpreting concerning posts to decide whether or not they are meaningful. Move directly to response. *Do you know any adults they would trust to help them?*	• Can you tell me a little more about the person who's posting this content? • Is the person posting this a friend, acquaintance, or somebody you know? • Do you know any adults or trusted friends who could help this person?	• I don't know if it matters, but I'm like not really good friends with them or anything. • I don't really know them or talk to them in person, but I know their coach from school. Should I tell them?
Clarify your role: Be clear about how you can help. Be sure to mention confidentiality and privacy, particularly if you are a mandated reporter. Reassure the viewer that you can take it from here.	• You did the right thing by reaching out. I will take it from here. You gave me enough information to follow up with their coach. • I will take it from here. We won't mention your name, they don't need to know that. So you can feel assured that your privacy will be kept.	• Are you going to tell anybody I told you? If ok, I'd like to just keep it between you and I. • So, what should I do now? • Are you going to reach out to them? I think you'd be way better at knowing what to do than me.
Follow-up: Thank the youth who found the concerning messages for reaching out and provide them with resources to feel more confident navigating future concerning posts. The website We R Native has fact sheets and videos for youth on this very topic [20], or Facebook offers safety tools [21]	• Are you feeling ok about the situation now that we've had the conversation? • I want to give you a few resources if you want to learn more about this topic: link to WRN[a]. • Facebook also has a tool: link that you can report concerning posts. • Again, thank you for reaching out and always know that you can reach out to me. I won't share your name with anyone else.	• If this happens again, are there any places that could help me respond? • Isn't there something on Facebook that I can use to report the post and FB can help them out? • I'm not sure if I feel comfortable reaching out if I see this again. Is there something else I can do?

[a] WRN: We R Native.

Procedures

Human Subjects Protections

The study protocol was reviewed and approved by the Seattle Children's Research Institute Institutional Review Board (IRB) and the Portland Area Indian Health Service IRB. Data collection took place between December 2016 and January 2018.

Recruitment

The Northwest Portland Area Indian Health Board recruited participants over a 2-month period using an online recruitment letter that described the training objectives and eligibility criteria. The form was distributed using a Constant Contact listserv and email listserv that reaches over 750 tribal health educators and adolescent health allies across the United States. Those interested in participating were directed to a SurveyMonkey link that confirmed eligibility criteria, followed by an electronic consent form, and a form to collect participant demographics. Demographics collected at this point included: name, tribe, organizational affiliation, state, number of years working with AI and AN youth, types and amount of suicide prevention training, and mailing address for US $15 incentive.

Interest forms were completed by 50 eligible educators living in the Pacific Northwest, including the States of OR, WA, ID, and by 23 educators living in other regions of the United States. Eligible participants included adults (≥18 years old) who mentored and/or regularly interacted with AI and AN youth.

All participants indicated they had access to a computer with internet to complete pre-post surveys and watch the video and had access to a mobile phone that could be used to carry out the interactive role-play scenario. In appreciation for their time, participants received US $15 after completing the intervention and US $15 after completing the 6-month follow-up survey.

Intervention Delivery

To begin the study, the research team sent participants a welcome email with a link to the Web-based training session and a reminder about using their unique identification. The training was available for participants to complete anytime during the 3-month window. Throughout the duration of the training period, the data manager checked for survey completion on a biweekly basis. Nonresponders were sent tailored reminders to complete the training and pre- and postsurveys up to four times over 3 months.

After completing the Web-based training session with 30-minute training video, participants were randomized using a blocked randomization process, into one of the two study arms (Textbox 1). Those in arm 1 proceeded with completing two follow-up surveys, the first at immediate follow-up and then again at 6 months. Aside from the follow-up surveys, participants randomized to arm 2 received an additional email from the team, scheduling the coached role-play within 2 weeks of the training. Each role-play was conducted with two to four researchers, who viewed the text message exchange in real time using a SMS dashboard and discussed possible responses before sending them to the participant. A short video clip that demonstrates successful application of the VCP during a concerning post scenario was emailed to participants after they completed the role-play.

To collect the 6-month follow-up data, the research team sent participants tailored reminders every 2 weeks, staggered by their training or role-play completion date, over a 3-month period.

Textbox 1. Participants were randomized into two study arms.

Study arm 1:

- Completed 1-hour webinar, including 30-minute video training
- Reviewed training handouts
- Immediate follow-up survey
- Six-month follow-up survey

Study arm 2:

- Completed 1-hour webinar, including 30-minute video training
- Reviewed training handouts
- Immediate follow-up survey
- Participated in coached role-play via text message
- Viewed 3-minute video clip of an exemplar role-play scenario
- Six-month follow-up survey

Data Collection Instruments and Data Handling

The pre-, post-, and 6-month follow-up survey tools were collaboratively designed by the two research teams. The key outcome measures for the training were changes in concerning post knowledge, intention to intervene, and self-efficacy associated with steps in the VCP. The surveys were collected electronically using Catalyst software. Catalyst is the secure, Web-based survey design and collection software used by the University of Washington and Seattle Children’s Research Institute. The software is approved by the University of Washington IRB and can be configured not to collect respondent IP addresses. Pre- and postsurveys were collected and managed using Catalyst.

The research team randomized eligible participants using three variables (previous suicide prevention training experience, current job role, and self-efficacy), using a cluster randomization by groups, into two study arms. Participants in arm 1 watched the 30-minute training video and reviewed accompanying handouts. Those enrolled in arm 2 watched the 30-minute training video, reviewed the training handouts, and participated in an interactive role-play with a coach that took place after the training, via text message.

Variables

Participants

The presurvey collected participant demographics, including gender, age, state of residence, race and ethnicity, and role in their organization or community. Demographic variables were summarized in terms of frequencies and percentages.

Intervention Usability and Appeal

The post survey included three quantitative measures of intervention usability and appeal, including (1) rate the quality of the training video (scale 0-6), (2) rate the quality of the training handouts (scale 0-6), and (3) would you recommend the training to others (yes, no)? At the end of the survey, participants were also asked to provide open-ended feedback on the (1) 1-hour webinar, (2) 30-minute video, (3) the training handouts, (4) a 30-minute coached role-play scenario, (5) the most valuable concepts or skills they acquired during the training, and (6) other ideas or suggestions to improve the training. The team synthesized open-ended responses to identify reoccurring themes.

Coached Role-Plays

The postsurvey included two quantitative measures assessing the coached role-play: (1) rate the quality of the coached role-play (scale 0-6), and (2) whether the coached role-play improved the training experience for the participant (yes, no). The investigators also conducted a content analysis of the coached role-play transcripts to evaluate participant adherence to the three steps of the VCP. A total of two trained coders developed a codebook to determine adherence to recommended VCP communication strategies. The research team then viewed the categories and coding system to verify consistency and accuracy, before coding took place. Responses were then analyzed across all role-play participants. The team also synthesized open-ended responses to survey questions, to identify reoccurring themes.

Measures of Training Effectiveness

Analysis of measures of effectiveness included paired *t* tests comparing difference of means for self-reported ratings before and after the intervention. The difference of means for self-reported ratings before the intervention and 6 months postintervention was compared using paired *t* tests.

Analysis

Survey Data Analysis

All survey outcome variables were summarized in terms of means and standard deviations. Absolute changes between pre- versus postintervention were calculated and evaluated using a paired *t* test. All reported *P* values were two-sided, and $P<.05$ was used to define statistical significance. Statistical analyses were performed using SAS software, version 9.4 (SAS Institute, Cary, NC) and R software version 2.15.1 [22].

Role-Play Content Analysis

A total of two researchers conducted content analysis on the role-play transcripts to assess participants' adherence to the skills and strategies recommended in the VCP. In addition, the conversational style of each participant was evaluated. To address adherence to the VCP, two trained investigators used a deductive approach in which the VCP informed *a priori* categories, that is, categories were developed before review of data toward capturing items under steps 2 and 3 of the VCP, from listen carefully to resources and tools. Items under step 1 were omitted, as these actions were intended as approaches to make the conversation more likely and would take place before the text message interaction. In addition, *Contact the person at risk* was omitted because the intention was for this step to take place after the initial conversation with the youth who viewed the concerning post.

To evaluate conversational styles, the two researchers used an inductive, open coding technique. An initial review of transcripts led to the development of categories informed by the data. The researchers used an iterative process of reviewing transcripts and refining the codebook until the categories were finalized, resulting in three categories. The first was Directive, in which the participant used an authoritative tone, giving instructions to the youth. The second was Collaborative, in which the participant sought consensus about a plan of action. The third was Noninclusive, in which the participant suggested a plan of action that did not involve the youth. Conversational styles were not mutually exclusive; some participants used more than one. For both content analysis techniques, interrater agreement was calculated using a 20% subsample of transcripts. For Assess Well-being of the Viewer and Gather Information, agreement was 88%. For all other variables, agreement was 100%.

Results

Demographics

Eligible prospective participants (N=73) included teachers, coaches, counselors, and tribal health personnel (personnel working with tribal communities), with varying levels of experience responding to someone with suicidal ideation. Most interest form applicants reported having 10 or more years of experience working with Native youth (41/73, 56%), followed by 1 to 5 years (16/73, 22%). Most reported using social media themselves on a daily basis (61/73, 84%) or weekly basis (8/73, 11%). Nearly one-third (22/73, 30%) reported having no formal training in suicide prevention or intervention skills; the remainder identified one or more trainings, including QPR (27/73, 37%), ASIST (27/73, 37%), Kognito (1/73, 1%), SafeTALK (11/73, 15%), Youth Mental Health First Aid (14/73, 19%), or Sources of Strength (2/73, 3%).

The blocked randomization process balanced the two arms in relation to experience working with AI and AN youth, experience using social media, and prior training in suicide prevention. Those who participated in the intervention and completed pre- and postsurveys were primarily female (64/73, 88%) and reported working in youth wellness or prevention; participants also included parents, coaches, teachers, and mental health professionals (Table 2).

Table 2. Demographic information for tribal health educator participants.

Demographics	All participants (n=41)	Participants who completed pre- and postsurvey (n=35)	Participants who completed, pre-, post-, and 6-month survey (n=22)
Gender, n (%)			
Male	5 (12)	5 (14)	4 (18)
Female	36 (88)	30 (87)	18 (81)
Job, n (%)			
Teacher or educator	8 (20)	7 (20)	6 (27)
Coach	4 (10)	4 (11)	3 (14)
Youth wellness or prevention staff	20 (49)	20 (57)	14 (64)
Nurse or clinician	2 (5)	2 (6)	3 (14)
Mental health professional	6 (15)	6 (17)	5 (23)
Parent	7 (17)	6 (17)	4 (18)
Other	19 (39)	16 (46)	8 (36)

Intervention Usability and Appeal

The immediate postsurvey was completed by 85% (35/41) of participants; the 6-month follow-up was completed by 71% (29/41). Almost half of the eligible participants completed the training intervention associated with their study arm (arm 1: 17/33, 52%; arm 2: 12/35, 34%), and 43% (29/67) completed the 6-month follow-up survey (arm 1: 17/33, 52%; arm 2: 12/35, 34%).

On a 7-point Likert scale (rating 0 as poor and 6 as excellent), participants gave the training video an average score of 5.32 (SD 0.78) and the handouts a score of 5.27 (SD 1.12); all participants indicated they would recommend the training to others.

When asked for open-ended feedback on the training, participants were enthusiastic about its utility and expressed they would recommend it to their peers:

> *I think the video was VERY well done! The personal experiences in the beginning with the Lukes family really engaged me and brought the severity of the topic home.*
>
> *I thought it was really good and would like to be able to use it for trainings of others and referral for people. I am a mental health practitioner suicide prevention, intervention, and postvention, and think it would be a valuable tool for me. Good job!*

Many offered helpful suggestions to improve the training materials:

> *The second half of the video could be expanded, to include more focus on Ask About Suicide (ASK) and QPR. Instead they were referred to and mentioned.*
>
> *Perhaps if a video was made that demonstrated the roleplay (like the one we did on the phone). That was really, really beneficial.*
>
> *Include additional visuals of emojis and statements used by youth.*

Others gave suggestions to support its dissemination in community settings:

> *Adapt the video for community presentations to educate parents and para-professionals.*

Six months after participating in the training, nearly all participants reported benefiting from the training and following its recommendations:

> *This training is excellent, especially for adults working with youth in contexts beyond social services. Being in Indian County involves many social, economic, educational, and recreational contexts. It is good that it offers training for people to effectively and proactively support our Native youth.*
>
> *The training was a great tool and discussion starter for folks in our community when I brought up the topic.*

Training Effectiveness

Our pilot evaluation of the effectiveness of the training included positive changes across several measures. A significant positive change was noted across all measures of confidence, including confidence starting a conversation with a youth about concerning posts on social media, intervening when a youth witnesses a concerning post by a family member or acquaintance, and confidence recommending support services to youth who have witnessed or posted a concerning message. Finally, participants reported improved confidence referring an at-risk youth to mental health services. In all cases, the difference of means between pre- and postsurvey was statistically significant, as noted in Table 3.

Table 3. Comparison of training effectiveness between pre- versus postintervention.

Variable	Preintervention, mean (SD)	Postintervention, mean (SD)	Change from pre- to postintervention, mean difference (SD)	*P* value
Difficulty supporting youth posting CSMM[a]	1.54 (1.62)	1.31 (1.32)	0.2286 (1.66)	.42
Difficulty supporting youth who saw CSMM	1.31 (1.47)	1.03 (1.27)	0.2857 (1.69)	.32
Confidence starting a conversation with youth about CSMM	4.09 (1.92)	5.17 (0.98)	−1.0857 (2.01)	.003[b]
Confidence intervening effectively when a youth witnesses CSMM by their families or friends	3.63 (1.99)	5.2 (0.96)	−1.5714 (1.99)	<.001[b]
Confidence intervening effectively when a youth witnesses CSMM by their acquaintance	3.29 (1.99)	4.94 (1.19)	−1.6571 (2.01)	<.001[b]
Confidence recommending support services to a youth who witnesses CSMM	4.06 (2.06)	5.43 (0.74)	−1.3714 (2.13)	<.001[b]
Confidence recommending support services to a youth who has posted CSMM	4.37 (1.9)	5.54 (0.66)	−1.1714 (1.99)	.001[b]
Confidence referring a poster of CSMM to a mental health professional within community	4.06 (1.89)	5.34 (0.76)	−1.2857 (1.71)	<.001[b]

[a] CSMM: concerning social media message.

[b] Statistically significant difference.

At the 6-month follow-up, we again identified positive changes in relation to the presurvey. These included sustained positive findings regarding contacting youth who posted concerning messages, confidence starting conversations with youth about concerning social media posts, confidence intervening when a youth witnessed a concerning post, and confidence referring youth who posted or witnessed concerning posts to a mental health provider. Furthermore, there were statistically significant increases in self-reported behavior, including bringing up concerning posts with youth and adults in their community. Each of these changes were significant, as noted in Table 4.

Table 4. Comparison of self-reported behavior from pre- to 6 months postintervention.

Variable	Preintervention, mean (SD)	6-month follow-up, mean (SD)	Change from preintervention to 6-month follow-up, mean difference (SD)	*P* value
In the last 6 months, how many times have you brought up CSMM[a] with youth in your community?	0.89 (0.87)	1.39 (0.86)	−0.5000 (0.86)	.007[b]
In the last 6 months, how many times have you brought up CSMM with adults in your community?	1.04 (0.83)	1.58 (0.99)	−0.5385 (1.10)	.02[b]
What percentage of youth believe it is appropriate to intervene when some posts CSMM?	4.58 (2.89)	5.66 (2.25)	−1.0769 (2.62)	.047[b]
What percentage of adults believe it is appropriate to intervene when some posts CSMM?	5.89 (3.22)	6.77 (2.56)	−0.8846 (2.72)	.11
Confidence contacting a poster of CSMM to assess their risk	3.74 (1.76)	5.12 (0.96)	−1.3846 (1.75)	<.001[b]
In the last 6 months, how many times have you intervened when a youth witnessed CSMM?	1.24 (1.76)	0.74 (0.73)	0.5000 (1.58)	.12
In the last 6 months, how many times have you recommended support services to youth when they witnessed CSMM?	2.58 (3.73)	0.93 (0.98)	1.6538 (3.38)	.02[b]
In the last 6 months, how many times have you referred support services to youth when they posted CSMM?	1.77 (3.15)	0.74 (0.83)	1.0385 (2.66)	.06
Difficulty supporting youth posting CSMM	1.58 (1.63)	1.31 (1.65)	0.2692 (2.15)	.53
Difficulty supporting youth who saw CSMM	1.24 (1.46)	1.00 (1.55)	0.2308 (2.10)	.58
Confidence starting a conversation with youth about CSMM	4.27 (1.72)	5.43 (0.81)	−1.1538 (1.78)	.003[b]
Confidence intervening effectively when a youth witnesses CSMM by their families or friends	3.93 (1.94)	5.43 (0.81)	−1.5000 (2.01)	<.001[b]
Confidence intervening effectively when a youth witnesses CSMM by their acquaintance	3.62 (2.03)	5.00 (1.17)	−1.3846 (2.00)	.001[b]
Confidence recommending support services to a youth who witnesses CSMM	4.31 (1.83)	5.50 (0.77)	−1.1923 (1.79)	.002[b]
Confidence recommending support services to a youth who has posted CSMM	4.54 (1.78)	5.58 (0.71)	−1.0385 (1.68)	.004[b]
Confidence referring a poster of CSMM to a mental health professional within community	4.35 (1.81)	5.54 (0.71)	−1.1923 (1.72)	.002[b]

[a] CSMM: concerning social media message.

[b] Statistically significant difference.

Coached Role-Plays

Among arm 2 participants, 18 completed the coached role-play, and they gave this training component an average rating of 5.38 (SD 1.02). All reported the role-play improved their training experience. Evaluation of the role-play transcripts found that participants followed some of the VCP guidelines more than others. All participants completed the *Listen Carefully* step. The next most commonly completed step was *Clarify Your Role*, taken by 89% (16/18) of participants, followed by *Ask about Relationship* and *Assess the Well-Being of the Viewer*, both completed by 83% (15/18) of participants. Over half (10/18, 56%) followed the *Gather Information* step. The *Resources and Tools* step was followed least often (8/18, 44%).

A total of three main response styles emerged: Collaborative (11/18, 61%), Directive (8/18, 44%), and Noninclusive (4/18, 22%), with 22% (4/18) of health educators using more than one approach. Collaborative approaches included shared decision-making processes and questions posed to youth confirming their support for a given follow-up plan. For example, one participant asked, “Would you feel comfortable approaching her B-ball coach…about the posts?” Directive approaches, by contrast, involved instructions given to the youth about how to proceed. An example of Directive message was, “Please be sure to contact an adult to support you—and check back in with me.” Finally, when using Noninclusive approaches, participants informed youth of next steps the adult participant would be taking without consensus seeking. One participant said, “I'll take care of following up and I'll talk to the coach or someone else who can help.”

Discussion

Principal Findings

This study assessed the usability, appeal, and impact of an hour-long training to prepare adults who work with Native youth to better support teens who post or view concerning messages on social media. Three major findings emerged in addressing this study purpose. First, participants provided feedback that included positive reception of the training. Second, findings supported positive effects of the training on participants' self-efficacy to address concerning social media posts. Third, analysis of the coached role-plays yielded opportunities for intervention improvements.

Our first major finding was that participants largely regarded the training intervention positively. After completing the training, participants expressed enthusiasm about its content and utility; 100% indicated they would recommend the training to their peers. Participants also offered helpful suggestions to improve the training materials, which have since been used to make updates and enhancements to the webinar, video, and handouts. These findings support the usability and appeal of the intervention.

Our second major finding was that significant improvements were noted across several measures of training efficacy that were retained even at 6 months, including contacting youth who had posted concerning messages, confidence starting conversations with youth, confidence intervening when a youth witnessed a concerning post, and confidence referring youth to a mental health provider. Most importantly, participants reported an increased number of clinical referrals 6 months posttraining, an important marker of training efficacy. These findings are consistent with previous studies using training as an intervention strategy. Previous studies supported Web-based gatekeeper trainings as effective suicide prevention approaches, particularly among adults serving AI and AN communities [4,23-26]. Our findings extend this work by supporting gatekeeper trainings as an effective approach to address concerning social media posts viewed by youth.

Our third main finding was that evaluation of the coached role-play revealed opportunities to improve the training intervention. As in our study, previous research has included a role-play component in gatekeeper trainings to prevent suicide [4,27,28]. Our study is unique in its inclusion of a text message–based role-play, as well as analysis of these conversations' transcripts to assess training outcomes. For example, analysis of this study's coached role-play suggested that participants' adherence to the VCP varied by step. Of note, less than half of participants shared VCP tools and resources. It is possible that participants felt unable to provide adequate resources related to mental health, given that nearly a third did not have previous formal training in suicide prevention or intervention. An alternate possibility is that adults may overlook this step in ensuring that they contact the youth who created the concerning post. Nevertheless, providing resources and tools to the youth who identifies the concerning post may be a critical task. Previous work has suggested that youth viewing concerning posts often do so alone, and they report a need for resources when they encounter such Web-based content [11]. Thus, future research is needed to examine barriers adults may face in offering resources during conversations about concerning posts, such as experience with formal training related to suicide prevention or intervention.

Further, analysis of the coached role-play revealed three communication styles when responding to youth who had viewed concerning posts: Collaborative, Directive, and Noninclusive. One possible explanation for the emergence of these three techniques is professional role and training. For example, a physical education teacher or coach may approach a conversation about a concerning social media post in a collaborative manner to provide support and encourage rapport in absence of specific medical training, whereas a school nurse may be more directive, having training and resources at their fingertips. These findings are important to consider in light of previous research on approaches to conversations about sensitive social media posts. Some evidence suggests that college students have preferences about how to conduct conversations related to concerning social media content [17,18]. Thus, the manner in which a tribal health educator approaches the conversation could have effects on the teen's well-being, as well as their willingness to collaborate to find help for the youth sharing concerning social media posts. Future research and improvements to the coached role-play component should address youths' preferred conversational styles and emerging research on effective messages and communication techniques.

Since the completion of the study, the training has been made available to tribal health educators at Healthy Native Youth website [19]. Strong interest and utilization (with over 750 YouTube video views), suggest that this Web-based training is an accessible, convenient format to build self-efficacy for busy adults who work with Native youth.

Limitations

Several important limitations were present in our study design. This study did not involve a control group and, as such, cannot determine the true effectiveness of the training intervention. The opt-in recruitment strategy also limits the generalizability of our findings, as those who agreed to participate are likely more aware of the importance of this topic than other adults who chose not to participate. In addition, our initial sample size was small; only 85% of participants completed the immediate postsurvey, and just over half of them completed the 6-month follow-up survey. This may have reflected a response bias among our respondents. In a more robust study design, special attention should be given to improve survey response rates and participant retention, especially if conducted over a longer period of follow-up.

Conclusions

Findings from this pilot study indicate that the *Responding to Concerning Posts on Social Media* training is a promising tool to better prepare adults to intervene and complete the three steps outlined in the VCP: (1) Start the Conversation; (2) Listen, Gather information, and Assess Viewer Experience; and (3) Plan and Act. To our knowledge, this is the first gatekeeper training for adults that provides guidance for responding to concerning posts on social media. Given the frequency of posts by teens and young adults that express suicidality and self-harm, this training may serve as a helpful blueprint for designing similar trainings for other high-risk populations. Additional research with a larger cohort of participants is needed to determine the unique impact of the coached role-play scenario on skill development, and changes in mental health referral rates, behaviors, and skills.

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Conflicts of Interest

None declared.

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Abbreviations

AI: American Indian
AN: Alaska Native
IRB: Institutional Review Board
QPR: question, persuade, refer
SAMHSA: Substance Abuse and Mental Health Services Administration
VCP: Viewer Care Plan

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Original Paper

Videoconferencing Psychotherapy in the Public Sector: Synthesis and Model for Implementation

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Abstract

Background: Videoconferencing psychotherapy (VCP) is a growing practice among mental health professionals. Early adopters have predominantly been in private practice settings, and more recent adoption has occurred in larger organizations, such as the military. The implementation of VCP into larger health service providers in the public sector is an important step in reaching and helping vulnerable and at-risk individuals; however, several additional implementation challenges exist for public sector organizations.

Objective: The aim of this study was to offer an implementation model for effectively introducing VCP into public sector organizations. This model will also provide practical guidelines for planning and executing an embedded service trial to assess the effectiveness of the VCP modality once implemented.

Methods: An iterative search strategy was employed, drawing on multiple fields of research across mental health, information technology, and organizational psychology. Previous VCP implementation papers were considered in detail to provide a synthesis of the barriers, facilitators, and lessons learned from the implementation attempts in the military and other public sector settings.

Results: A model was formulated, which draws on change management for technology integration and considers the specific needs for VCP integration in larger organizations. A total of 6 phases were formulated and were further broken down into practical and measurable steps. The model explicitly considers the barriers often encountered in large organizational settings and suggests steps to increase facilitating factors.

Conclusions: Although the model proposed is time and resource intensive, it draws on a comprehensive understanding of larger organizational needs and the unique challenge that the introduction of VCP presents to such organizations.

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KEYWORDS

implementation science; videoconferencing; psychotherapy; public sector; telemedicine; mental health

Introduction

Background

The provision of health care services on the Web via real-time video communication is growing [1,2]. In the delivery of mental health care services, particular growth has been seen in the form of videoconferencing psychotherapy (VCP) [3]. VCP is appealing because it emulates the face-to-face delivery of traditional in-person treatment, while offering a number of potential advantages, including increased flexibility and reach. Moreover, VCP has the potential to overcome challenges, such as time constraints, scheduling difficulties, and client concerns about treatment-seeking stigma, by allowing clients to engage with professional services in the privacy of their own home [4-7]. Arguably the greatest advantage of VCP is its ability to overcome access-to-care barriers for those in underserviced regions. This advantage makes VCP an attractive service offering for organizations that serve geographically disperse or isolated populations, such as military personnel, veterans, prison inmates and staff, first responders, mining workers, or people living in rural or remote locations [8-10].

Although a growing body of research has found VCP to be effective [11], studies have also reported difficulties implementing the modality, with VCP researchers and experts expressing concerns at how VCP initiatives often fail to progress past the pilot phase to implementation on a wider scale [12-14]. This is partly because of the nature of the organizations themselves—large geographically dispersed health care organizations where the complexity of implementation is often underestimated [14,15].

It appears that introducing VCP services within organizations already providing services can be quite disrupting as implementation and governance of VCP requires input from a wide variety of parties (eg, the health care providers, funding bodies, and software providers) and personnel (eg, clinical staff, information technology [IT] staff, management, and policy makers). Therefore, VCP implementation in public sector settings represents a significant multifaceted challenge, requiring various changes and collaborations that have implications at an individual and organizational level. A potential explanation for the lack of successful widespread implementation in these settings may be because of a lack of clarity around how to best implement and sustain VCP modalities in real-world settings. Although considerable research has been conducted, examining the effectiveness of VCP [11] and developing best practice guidelines [16-18], there does not appear to be a clear consensus as to how best to implement such services. This has led to researchers calling for rigorous implementation models to be developed and tested [14,19-21].

This Study

This paper aimed to synthesize the findings and lessons learned from previous implementation attempts into a cohesive and integrated model, specifically for the implementation of VCP in public sector organizational settings. In addition to previously developed models and best practice guidelines, the model proposed here draws on the barriers and facilitators for the implementation and delivery of VCP identified in earlier papers, as well as the solutions developed.

Methods

To develop a comprehensive and cohesive model for VCP implementation, this study utilized an iterative search strategy to bring together insights from mental health, IT, and organizational psychology. As such, a broad range of search terms, including (but not limited to) variations of implementation, videoconference, psychotherapy, mental health, and telehealth, were entered into searches across PubMed, PsycINFO, and Web of Science databases. This study focused on synthesizing the barriers and facilitators of VCP implementation, identified in previous studies and the previous models presented for VCP implementation in large or public sector organizations. Our model also incorporates learning from other fields of research (eg, IT and organizational psychology) in the emergent recommendations.

Results

Brief Review of Barriers and Facilitators of Videoconferencing Psychotherapy Implementation

A review of the VCP literature revealed that there are several barriers to implementing this modality in public sector organizations. Common barriers to VCP implementation efforts include clinician attitudes and availability, as well as technological and logistical issues [12,22-24]. Additional barriers for public sector organizations implementing VCP services include concerns regarding clinical risk management and data security, resource and funding constraints, regimented protocols, and geographically dispersed service providers [4]. For example, Brooks et al [25] surveyed 39 stakeholders who were involved in the implementation of VCP services for veterans in the United States. Respondents noted many challenges with the implementation process, including staffing issues, setting up the VCP infrastructure, obtaining trust and acceptance of the new technology from staff and clients, and recruitment. Similarly, Adler et al [26] conducted a pilot study, investigating VCP implementation for the US Department of Veterans' Affairs (VA). Interviews with clinicians involved in the study found that all 6 sites suffered delays to implementation because of unanticipated organizational constraints (eg, limited space, misplaced equipment, and difficulties setting up and supporting new technology). Further barriers included inadequate staffing, delays in staff training and poor communication with clinical personnel regarding priorities and workload, as well as issues with staff changes.

Although much of the research investigating VCP implementation has originated in the US VA [12,22,25-31], there are several further organizational contexts in the public sector where VCP has been implemented, such as schools, hospital emergency departments, and palliative care settings [32-34]. For example, Donley et al [33] investigated VCP implementation in an emergency department. The authors highlighted several factors that are important to consider in terms of implementing VCP in this setting, such as reviewing the technology and resources required and staffing considerations. Furthermore, the authors highlighted that, as the use of VCP is a relatively new process in the ED, guidelines and policies will need to be developed. The authors also noted the importance of ensuring that the development of workflow processes is contributed to by all the teams involved in VCP and that this should involve clear communication regarding roles and responsibilities.

Brief Review of Previous Implementation Models

Shore and Manson [10] provided an early attempt at prescribing a model for VCP implementation in rural US settings for veteran American Indians. This model included 6 stages: (1) establishing the willingness of the target population to engage with the modality, (2) a survey of resources required for implementation, (3) consideration of the involvement of external parties, (4) drafting protocols and assigning roles, (5) an initial pilot study, and (6) complete integration within the organization. This model was found to be successful in implementing and sustaining VCP in the US VA [10]. Shore and Manson [10] highlighted that the timeline for implementation at each site was largely dependent on the participation and buy-in from staff within the various sites. In their case, stages 1 to 4 took 12 months, whereas the pilot study (stage 5) lasted 6 months. This was the only previous model specific to VCP implementation found in our review.

A lack of models specific to VCP implementation has lead organizations and researchers to adopting general implementation and evaluation frameworks. More recent VCP implementation studies have adopted the Promoting Action of Research Implementation in Health Services (PARIHS) implementation framework [12,27,35,36]. Kitson et al [36] summarize the PARIHS framework according to 3 key features.

- Evidence: knowledge gathering and engaging leadership, conducting a needs analysis, and identifying initial barriers and facilitators relevant to implementation.
- Context: investigate the quality of the environment or setting where implementation is occurring.
- Facilitation: a strategy that allows interventions to be tailored to enable change and make adoption of a new practice easier.

Implementation success is then defined as a function of these 3 features and the interrelationships among them.

The PARIHS framework has previously been used to implement new services in the public sector. For example, Crowley et al [37] conducted a pilot study to evaluate the feasibility and effectiveness of using existing US VA clinical staffing and equipment to deliver a home-based telemedicine intervention for veterans with diabetes. In their study, the intervention was implemented by members of the US VA (internal facilitators) while the evaluators (external facilitators) managed the research tasks (eg, randomization, outcome analysis) [37]. Other research at the US VA has also employed PARIHS successfully by dividing the facilitation role between internal and external facilitators [27,35].

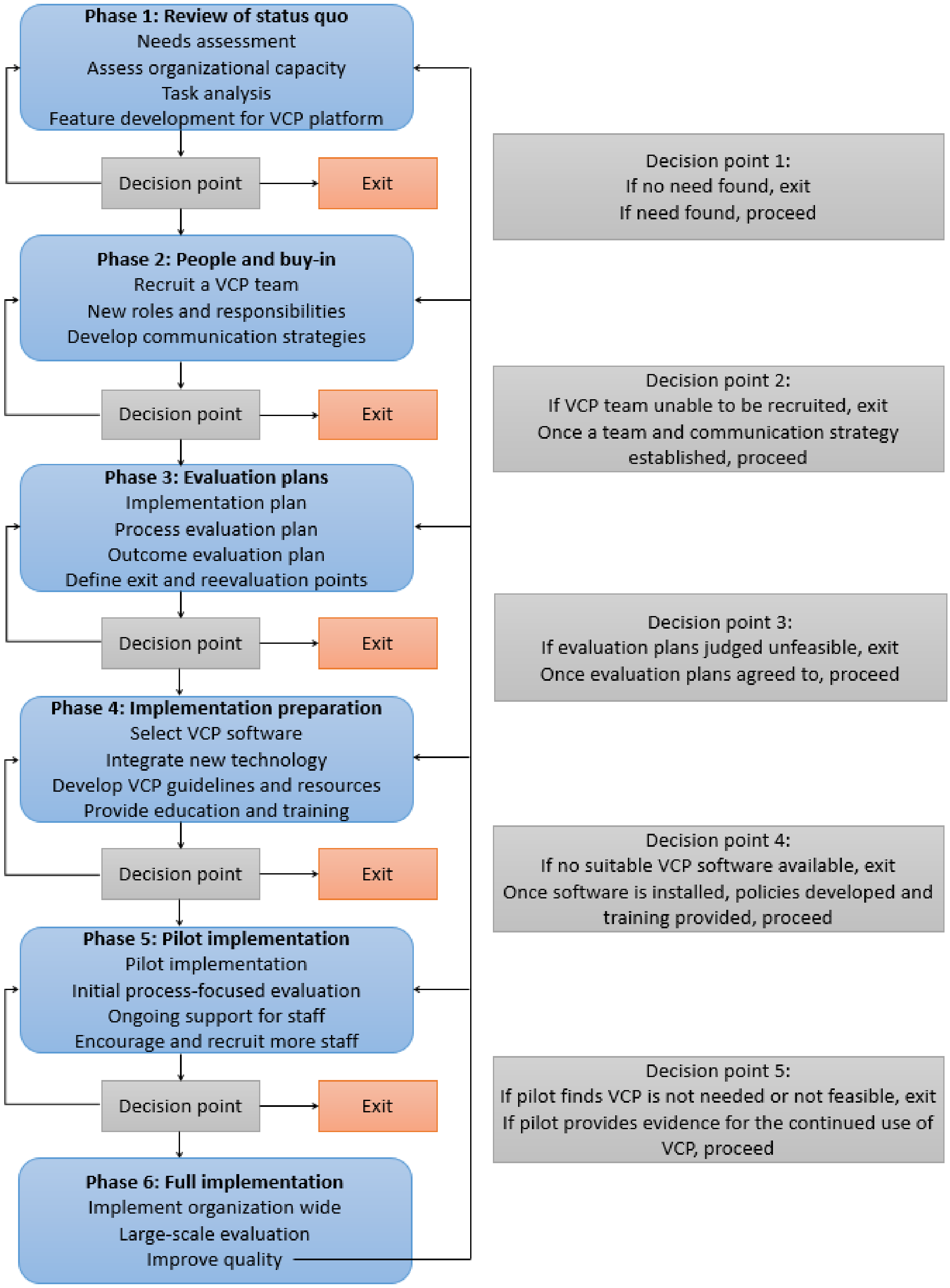
Although some studies have reported successful implementation using PARIHS, few studies have been found to have used this framework prospectively to design implementation strategies [38]. Furthermore, although one of the greatest benefits of the PARIHS framework is its flexibility and applicability to a variety of different contexts and settings, this can also be seen as a limitation. A review of current evaluation frameworks found that the PARIHS framework was not suited to guiding evaluation, identifying key stakeholders, or generating transferable lessons [38]. An additional limitation of PARIHS is the lack of clarity concerning precisely how the features of the framework facilitate the adoption of interventions on a broader scale (ie, at the organizational level) [39].

A Proposed Model

From the broader VCP literature and the recommendations made from previous VCP implementation efforts, the following model for the implementation of VCP in public sector health care settings has been formulated. The model has been informed by the latest American Telemedicine Association (ATA) and American Psychological Association (APA) VCP service delivery guidelines [17], as well as the PARIHS and the Shore and Manson [10] implementation models. A detailed overview of the model is provided in Multimedia Appendix 1, which maps the stages and features against previous implementation models, frameworks, and the recommendations of the ATA and APA. Organizations wishing to follow the model can use the VCP Implementation Checklist we developed (see Multimedia Appendix 2).

As shown in Figure 1, the model involves 6 phases: review of status quo, people and buy-in, evaluation plans, implementation preparation, pilot implementation, and full implementation. Working from top to bottom, we describe the major components of the model, and we provide the rationale and relevant literature supporting each step that has been integrated into the model on the basis of the barriers and facilitators encountered in previous research and the models and frameworks used to guide previous implementation initiatives. The model was developed using the cyclical organizational participatory research framework [40]. As indicated by the feedback arrows in Figure 1, the model employs a cyclical and iterative processes that enable organizations to engage with key stakeholders and collect and use data at each stage to help organizations reflect on and integrate findings to improve the process.

Figure 1. Model for videoconferencing psychotherapy implementation. VCP: videoconferencing psychotherapy.



Phase 1: Review of Status Quo

A prominent takeaway from the literature is that before any form of implementation can begin, extensive preparation is required. Doing this work before introducing VCP allows the challenges that have been reported in previous implementation attempts to be identified and addressed. To achieve this, phase 1 has been divided into 4 steps: (1) needs analysis, (2) organizational capacity for change, (3) task analysis, and (4) feature development.

1.1. Needs Assessment

The initial step is to confirm that there is a need for a VCP service and that implementing such a service will fill a gap in the organization’s current service offering. A formal needs analysis can be conducted using a quantitative, qualitative, or mixed approach [41]. As a minimum, the needs assessment should investigate the target population's experiences and needs, as well as their service delivery preferences and self-efficacy with videoconferencing technology. The organization will then be able to determine whether a VCP service is needed and compatible with the organization's mission and target population.

1.2. Assess Organizational Capacity

After confirming that there is a need for a VCP service to be implemented, the organization needs to assess its capacity for implementation. Common barriers to the implementation of VCP identified in the literature are technological issues, organizational cultures, clinical workflows, and staffing issues [29]. Therefore, this assessment will be a multifaceted investigation of the technological, environmental, and human resources that are currently available within the organization and what additional resources will be required to implement the VCP service.

Various instruments have been developed and validated to assess an organization's capacity or readiness to implement telehealth services. A review of telehealth service implementation frameworks [14] highlighted the readiness assessment tool that was developed by Khoja et al [42]. This quantitative measure covers 5 categories of implementation: core readiness, technology readiness, learning readiness, societal readiness, and policy readiness. Organizations should consider adapting this tool to assess their capacity for implementing VCP.

1.2.1. Technological Capacity

Before attempting to implement VCP, the organization will need to assess its technological capacity at the micro and macro-level. At the microlevel, the organization will need to ensure that they have the necessary hardware and mobile technology, as well as sufficient internet capacity. With regard to hardware and mobile technology, the organization will need to ensure that any existing resources (eg, desktops, laptops, and tablets) are equipped with high definition video cameras and audio systems (eg, microphone, external speakers, or headphone accessories). If these features are not built into these devices, they can be added by using external webcams and microphones via USB.

At the macro-level, the organization will need to ensure that their information and communication technology infrastructure is adequate to support a VCP service. Specifically, the organization will need to ensure that the capacity of their internet will be able to provide uninterrupted video communication. A minimum bandwidth of 384 kbps is recommended for conducting VCP [16]. Importantly, the organization will need to ensure that the equipment used to conduct VCP meets the Health Insurance Portability and Accountability Act (HIPAA) requirements, as well as local privacy and data security policies (more information in 4.1 Select Videoconferencing Psychotherapy Software).

1.2.2. Environmental Capacity

In addition to ensuring the organization has the technological infrastructure required to implement VCP, the organization will also need to ensure that adequate space is available to engage in the modality. This may require dedicating a room to VCP. The location chosen to conduct VCP sessions should be well lit and isolated, to limit visual and audio distractions and assure privacy.

The organization will also need to consider the resources available in the community of the target population. To engage in the VCP modality, clients will require the necessary hardware and internet capacity. If the target population is unlikely to possess the hardware or internet capacity (a likely problem for those living in rural and remote locations), alternative arrangements will then need to be considered. The organization will need to determine whether they have the capacity to distribute hardware to clients. If not, organizations may then need to reach out to local community centers (eg, health clinics) that possess the required hardware and capacity (ie, hardware, internet, and room) to enable clients to visit and engage in VCP safely.

1.2.3. Human Factors

With regard to human resources, the organization will need to consider the current capacity of its clinicians to provide VCP. This will involve ensuring that VCP can be introduced so as not to overload clinicians, as well as assessing their readiness to engage in the new modality. Although similar to traditional in-person service delivery, clinicians may not feel prepared to engage in the VCP modality without first receiving some form of formal training. As a result, organizations can likely expect clinicians who have not previously used VCP to have negative attitudes toward the modality.

Previous research has shown that clinicians who have not experienced VCP appear to have more concerns about its effectiveness and the organization's need for the modality [22,25-27]. For example, clinicians may hold concerns around the effectiveness of the modality, impact on the therapeutic relationship, their familiarity with the technology, dealing with high-risk clients, and concerns with data security issues [43,44]. Therefore, it is recommended that organizations investigate clinician experiences, perceptions of VCP service need, and preferences (or willingness) to engage in a VCP modality.

Clinicians will not be the only ones whose workflow will be disturbed. Clerical and IT workers will also be affected by the introduction of a VCP service. The capacity of the IT support staff to implement, monitor, and provide support for a VCP service will need to be considered. Previous research has found that logistical problems (eg, inadequate staffing, scheduling, overwhelming workloads, and staff changes) are common barriers to VCP implementation [29,45]. Therefore, the introduction of VCP may fundamentally alter the tasks and activities staff perform while delivering in-person services.

1.3. Task Analysis

To assess the human factors and help facilitate later phases in this model, particularly around software selection (4.1 Select Videoconferencing Psychotherapy Software), it may also be useful at this stage to work with clinicians and administrators to generate an in-depth understanding of their daily workflow and key operational tasks in relation to client contact.

A task analysis can be conducted using interviews, focus groups, and structured questionnaires, and it can be documented in writing or diagrams. The primary purpose of these activities will be to generate a features list, identifying the core tasks clinicians and administrators currently perform to deliver services that will need to be supported by the future VCP platform. This involves staff outlining the specific steps they take (both mental and physical) to achieve specific goals [46,47]. For counseling tasks, this could be the following: (1) checking a calendar that is populated by a receptionist for upcoming appointments, (2) accessing a physical client file from a filing cabinet, (3) creating a session plan, (4) going to the waiting room to welcome the client, (5) conducting a session, (6) updating the physical client file, and (7) returning the client file to the filing cabinet. Although this is a broad example, the outcome of this process is a detailed list of activities, currently used tools or software, and relationships among individuals required to complete certain goals. Quantitative measures can also be utilized to complement the task analysis.

1.4. Feature Development for Videoconferencing Psychotherapy Platform

The results from the task analysis can then be used to generate a features list of the core requirements that a VCP platform must have (or can be modified to have), to reduce the friction of adoption at later points. Using the previous example, features for a future VCP platform could include the following: (1) a calendar booking system accessible by clinicians and receptionists, (2) secure Web-based storage for client files, (3) a virtual waiting room for clients, and (4) the ability for the clinician to choose when to start and end a VCP session. A secondary gain of this process is the opportunity to identify pain points for the staff in their current tasks and activities (things that do not work well, are burdensome, or are time consuming) and investigate ways of reducing these pain points through feature selection for the new VCP platform.

The outcomes from this phase will help the organization identify whether the implementation of VCP is feasible and realistic, and these will ensure that the organization is in a better position to determine what protocol and policy changes are needed to facilitate the introduction of VCP. The required content, along with intensity and delivery preferences of training resources, should also be identified at this stage. Finally, addressing relevant human factors at this stage will be helpful to the organization to ensure that any concerns clinical, clerical, and IT staff have are addressed before the time comes to recruit clinicians and communicate the implementation strategy.

Phase 2: People and Buy-In

As discussed, an organization might expect some resistance to VCP implementation from clinicians. If drastic changes from previous protocols are required, the changes may also result in resistance from clerical and IT staff. Therefore, it will be important that the organization manages this change effectively and is able to foster buy-in for the VCP modality.

The Diffusion of Innovation theory is a valuable change model for guiding technological implementation initiatives. This theory appears particularly relevant to VCP, as it highlights the importance of communication and peer networking while accepting that not all organization members will adopt the new modality immediately [48]. The theory posits that an initial few people will be open to the new technology and adopt its use before more people become willing to try and eventually adopt the technology. This phase has been broken down into 3 steps in an attempt to apply this theory: (1) recruit a VCP team, (2) new roles and responsibilities, and (3) develop communication strategies.

2.1. Recruit a Videoconferencing Psychotherapy Team

Implementation initiatives in public sector health care organizations are often at risk because of their complicated bureaucracies. Given the multifaceted and cross-collaborative nature of VCP, coordination could prove to be particularly difficult and time consuming, putting the implementation of the service at risk [30]. To overcome this challenge, a critical step for implementing VCP is the recruitment of a motivated and stable (ie, permanent) team to lead the implementation. These individuals can be viewed as change agents, and they will predominantly be responsible for identifying and engaging with key stakeholders and developing a positive VCP culture [49].

Given the cross-departmental collaboration required to implement VCP, it will be important to ensure that each department within the organization is represented on the team. The composition of this team should therefore include organizational leaders, clinicians specializing in the offering of VCP, on-site VCP champions who encourage and promote VCP to clients and clinicians, IT support staff, and clerical staff representatives. Involving representatives from each department will help ensure that all parts of the organization have a voice in the implementation process. External representatives may also be recruited as consultants if an organizational need for this is identified in Step 1.2 (Assess Organizational Capacity).

It is important for these team members to be dedicated and committed to the implementation process. This team will need to appoint a leader who is ultimately responsible for coordinating the implementation. This person should have the authority to execute any decisions made across the organization. Given the time-intensive nature of implementation, the person assigned this role may need to make the management of the implementation his or her full-time role.

2.2. New Roles and Responsibilities (and Personnel)

The introduction of VCP will likely bring about changes to the roles of current clinical, clerical, and IT staff [50]. The organization will need to be transparent and work closely with existing staff to effectively manage these changes.

2.2.1. Videoconferencing Psychotherapy Champions

Program champions have long been recognized as critical resources for implementation [51]. Previous VCP implementation studies have found champions to be vital facilitators [10,12,22,25,27,52]. VCP champions will play a key role in providing ongoing support and information to participating personnel, acting as a communication bridge between the staff on site and those in key management positions, relaying concerns and directions accordingly. Champions may take on additional responsibilities, including potentially hosting VCP training and personal development seminars for clinicians.

The champions will need to foster a sense of enthusiasm toward VCP at the clinic level. This may be a challenge, given some clinicians may be skeptical of the modality. But if successful, the champion will lend support to the credibility, trial, and eventual adoption of VCP. To be successful, champions should exhibit homophily (ie, high similarity with other staff), empathy, and openness [49]. For large organizations with multiple, geographically dispersed service providers, it is recommended that each provider nominate its own VCP champion.

As staff concerns may center around VCP use in practice, when feasible, it may be useful for champions to gain some experience in conducting VCP themselves, before the initiation of the implementation, so that they can speak to their colleagues from experience. Once the VCP software is installed, champions may consider using the software to perform everyday tasks (eg, conduct meetings with other staff). Using the software in this way, in a low-risk environment, may be beneficial for increasing staff confidence with the technology.

2.2.2. Telehealth Coordinator

Introducing VCP may also create opportunities for new roles within the organization. An example of such a role is a telehealth (or VCP) coordinator. This person will be responsible for managing the VCP technology and process (eg, alleviating technical difficulties and managing appointments and consent forms).

It is recommended that organizations employ a technician dedicated to VCP, as previous studies have found that such roles help facilitate implementation [27,52]. This role may be filled by an existing staff member who possesses the knowledge and passion for the VCP modality. Alternatively, the organization may need to advertise to fill such a role.

2.3. Develop Communication Strategies

Communication channels will be needed so that concerns and solutions to any difficulties encountered during the implementation of VCP can be communicated effectively. Communication deficiencies have been identified as a key barrier in previous implementation studies [53]. This may be particularly true for VCP implementation efforts, as implementation will involve a variety of individuals from different departments, including clinical, clerical, and IT staff, as well as center management and organizational leaders. Therefore, the fostering and development of communication channels among these stakeholders, as well as clients, is another important step.

The first important point of communication will be to apprise clinicians and clients of the need for VCP. Communicating this need will require a strategy that is consistent over time and geographical region. Visits to participating clinical sites and regular teleconference calls with clinicians and meetings with clinical advisory committees have been reported to be helpful for ensuring successful implementation [10,35]. Messages related to the progress of VCP implementation should also be a standard agenda item at clinical meetings and appear in newsletters or bulletins prepared for clinicians and clients. Additional communication strategies for promoting VCP to clients include promotional materials and expressions of interest via the organization’s social media channels, webpages, and newsletters, as well as signage and materials (eg, brochures) within facilities and presentations at local community events.

Phase 3: Evaluation Plans

Timelines reported in implementation studies to date suggest that it may take between 1 and 12 months for activities in phases 1 to 4 to be completed [10,37]. Therefore, extensive preparation and forward planning are essential for the success of VCP implementation. This will require the organization to develop an implementation and evaluation plan by using a logic model, with goals and objectives for the new service, and a set of key variables (or success indicators) to be used to evaluate the implementation and effectiveness of the VCP service. Organizations should use this plan to assign the timeframe for each activity, as well as the specific personnel responsible for each activity. To enhance buy-in, all stakeholders should be involved in the development and approval of this plan.

3.1. Implementation Plan

The implementation plan should contain a project timeline, which lists the processes and milestones required to (1) install the VCP technology (see 4.2 Integrate New Technology) and (2) collect data for an evaluation (see 3.2 Process Evaluation Plan) and explain how the activities will be delivered within the stipulated timeframes. It is recommended that organizations employ a staged implementation approach. VCP should initially begin at a single site before being introduced more extensively throughout the organization’s other service providers. This approach has previously been found to be effective for implementing VCP services in public sector organizations [10,27,52], and this approach has several advantages over simultaneous implementation approaches. For example, a staged approach starting at a single location affords the organization the opportunity to gain meaningful insights into implementation processes that can later be applied on a larger scale. Such an approach also ensures that implementation can be tailored to accommodate the unique characteristics and available resources for each site. This planning phase will also help foster confidence in the efficacy of VCP, and, if seen as successful, this may promote the adoption of VCP by more clinicians and clients.

There are several factors that an organization should take into consideration when selecting a site for pilot implementation. These include the human, organizational, and community factors identified in Step 1.2 (Assess Organizational Capacity). The selected center should have the greatest readiness for VCP implementation. This means that the selected site must have personnel (ie, clinicians, clerical, and IT staff) who are available and willing to implement VCP. For example, the readiness of clinicians, in terms of experience or openness to adopting new technology needs consideration. Selecting a site with clinicians who are more amenable to VCP and more experienced in its use will assist the initial implementation of the service. The selected site will also need to have the necessary resources to deliver VCP (eg, computer hardware and space). The local client demand for VCP should also be considered. Demand may be higher for sites with a higher level of clinical need or where clients may find particular value in therapy via a Web-based modality (eg, in sites serving individuals in rural or remote locations).

3.2. Process Evaluation Plan

Evaluation forms a key part of monitoring implementation and determining its impact. Evaluation can be divided broadly into 2 activities, which might be a focus during different stages of implementation: process evaluation (investigating the successfulness of the implementation) and outcome evaluation (investigating the impact of the VCP service).

The evaluation plan needs to be considered at an early stage so that appropriate baseline measurements can be incorporated into service delivery. The process evaluation will encompass collecting data from those involved in the implementation to determine how the intervention was actually implemented. Data collected should aim to answer questions regarding the success of the implementation; the following are examples of such questions: Has VCP been implemented as intended? Were there any unanticipated barriers to implementation? How could implementation be improved? Are additional resources required for clients, clinicians, or administrative staff? Is it feasible to expand the service to other sites?

3.3. Outcome Evaluation Plan

On the contrary, when considering the outcomes of implementation, questions may include the following: Has availability of VCP increased delivery of therapy? Are treatment needs better met in particular groups that were hoped to benefit from greater accessibility of VCP (eg, persons in rural or remote areas)? Are clients satisfied with VCP? Is overall satisfaction with the service improved in people who have accessed VCP? Does receipt of VCP result in improved clinical outcomes?

Many of these questions can be answered by comparing the outcomes for a group of VCP clients to control groups. However, whether and how to use control groups for VCP evaluations require some careful consideration in relation to constraints of how feasible comparisons will be when considering anticipated numbers, sources of error and bias, and the statistical reliability of measurement.

3.3.1. Outcome Evaluation Data Considerations

Evaluation implicitly involves comparison, which may be defined in terms of change over time (eg, is delivery improved on some metric relative to previous indicators?) or between parallel versions of service delivery (eg, does the addition of VCP improve individual outcomes compared with routine service delivery?). Collecting these data may require planning to administer a measure during a baseline period before VCP implementation for comparison or to a group that is not receiving VCP to provide comparison data for the evaluation. Metrics, such as receipt of VCP or in-person therapy, may be relatively easily captured, but satisfaction and clinical outcomes may require incorporating new measures into practice.

Measures of uptake or delivery of therapy should be simple enough to collect routinely and accurately. If VCP supplements in-person therapy, pre-post implementation comparisons of total therapy delivery are likely to be meaningful. Such comparisons might be strengthened by obtaining data from a site not yet offering VCP to control for the effects of other organizational or external changes that may arise during the implementation period (eg, change in management or referral pathways).

However, achieving sensitive measurement of client clinical outcomes may be more challenging. Although clinical outcome measures may already be routinely administered, there may be significant missing data, resulting in systematic bias if there is a lack of follow-up data on clients discontinuing therapy. Client and intervention heterogeneity may mean that broad catchall measures of clinical outcome or quality of life need to be used. Universal measures, such as general well-being, overall symptom measures (eg, the Depression Anxiety Stress Scale; the Brief Symptom Inventory), or mental health–related quality of life (eg, The World Health Organization Quality of Life, Assessment of Quality of Life-8D) may be suitable for capturing outcomes across a number of client groups. However, it should be noted that the use of broad measures can mean reduced sensitivity to individual outcomes. Considerations in providing more sensitive measures include reviewing the most tailored measures, focusing evaluation on a specific subgroup where more sensitive measures can be used, resourcing personnel to ensure measures are administered, and follow-up with clients who discontinue therapy. A comparison group of clients not receiving VCP at another site might be used to control for the natural course of improvement under treatment as usual. However, given that effect sizes for many in-person psychotherapies are in the small-to-moderate range under trial conditions [54], in practice, it may be difficult to differentiate effects of VCP from site differences and other sources of error. Therefore, there may be value in adopting a randomized controlled design during a stage of the implementation, comparing with a treatment-as-usual or waiting-list group to control for the natural course of improvement.

3.3.2. Outcome Evaluation Design Considerations

Alternative designs, such as quasi-experimental designs, may be considered. Although these methods are not without their limitations, such as selection bias, they may provide valuable insight into differences between the effectiveness of VCP and in-person therapy. Other possible designs include the regression-discontinuity design and interrupted time-series design [55]. Psychological interventions typically produce small incremental changes in outcome measures, which may require several hundred participants to make meaningful between-group comparisons. Therefore, consideration to whether it is realistic to obtain sufficient data for comparisons to be meaningfully made is required.

In services that are introducing VCP as an alternative to in-person therapy, although it may be tempting to compare modalities to determine whether equivalent outcomes are produced, it should be noted that demonstrating noninferiority of an intervention requires higher statistical power than a superiority comparison [56]. As any differences on the basis of mode of delivery are likely to be very small, they are likely to be obscured by error and bias, unless a highly rigorous randomized controlled trial design were possible with a very large sample. In making comparisons between VCP and in-person therapies, it may be more realistic to compare metrics more proximal to the process of therapy, such as satisfaction and working alliance ratings.

3.4. Define Exit and Reevaluation Points

It is also important to consider the steps to be taken following data analysis. Results should, where possible, feed into the decision-making process when moving between steps in this model (Figure 1). There may be a number of critical decision points for each organization at which the results obtained through evaluation suggest the next steps to be taken. Articulating these steps and integrating them into the implementation and evaluation plan may save larger organizations time and resources at later points by clearly identifying the thresholds at which the implementation (1) proceeds to the next step, (2) regresses to an earlier step to reevaluate and adapt from the learnings of the most recent evaluation (eg, consider a different software selection), or (3) exit if the implementation does not appear to be feasible in the current organizational environment. These decision points allow the model to be flexible to changing needs and explicitly introduce feedback loops that may be useful for the ongoing quality assurance of the software system and service provision.

Phase 4: Implementation Preparation

This phase involves organizing all the appropriate resources for VCP implementation. Any gaps between the current and required resources identified from the assessment of organizational capacity should be acquired before any implementation attempt.

4.1. Select Videoconferencing Psychotherapy Software

The most critical resource to acquire will be the software platform to facilitate the VCP service. This choice is not simply a matter of cost. To aid in decision making, a features list (generated in Step 1.4 Feature Development for Videoconferencing Psychotherapy Platform) can be used to map existing software platforms against the core requirements and nice-to-have features of the organization (ie, clinician and clerical staff wish lists). This features list should have input from all relevant stakeholders and may require some specialist input (eg, lawyers to advise on appropriate terms of use).

This highlights the need for organizations to reach out to potential software providers to determine which one will provide the best fit. Organizations may wish to consider creating a shortlist of potential providers and making contact with each to discuss items regarding system integration (eg, customer support, access to resources, and customization) to help determine the best choice. The organization will also need to consider the security of each platform and the user experience each platform offers.

4.1.1. Data Security

Data security and bandwidth should be kept at the forefront of the decision making when selecting a suitable platform. Data security is a particular concern in any health care setting, as it is the organization's responsibility to ensure that client health data are kept confidential. Similar to any Web-based service, VCP brings a range of data security risks with regard to computer-mediated communication. For clients, concerns may revolve around geolocation vulnerability and hacking. However, these issues are likely only if one's computer is compromised rather than the actual software and having an up-to-date antivirus program should alleviate these concerns.

A more significant concern for organizations revolves around data encryption and the transference of data involving third parties. The organization should ensure that the technology meets relevant privacy requirements, such as HIPAA standards for protecting health information that is held or transferred in electronic form. Currently, there are a number of HIPAA-compliant platforms available to organizations for conducting VCP, including the following: VSee, Cisco (Cisco Systems, Inc), Polycom (Plantronics, Inc), and CoViu. Skype for Business (Microsoft Corporation) is also HIPAA-compliant, as is Zoom (provided the organization signs a Business Associate Agreement before use). Organizations are encouraged to consult their own IT experts to investigate the different VCP platforms before deciding which would be the best fit for the organization.

It will be the organization's responsibility to communicate risks to clients and have measures in place to mitigate the security risks outlined above. To overcome technology obstacles, it is recommended that binding contracts are put in place for ongoing support and continuity of service, data security, and technical support. Such contracts would protect against severed services and ensure that technological support is available to the organization when needed.

4.1.2. Usability

Another critical and often overlooked consideration is the software's usability. End users for VCP can include clients, clinicians, administrators, and IT support. It is possible for a software platform to meet organizational and legislative data security requirements, but it is also possible for it to be too challenging to learn, use, and adapt to the daily tasks and processes of staff. Trialing a variety of software platforms in low-risk environments (eg, to conduct remote team meetings) may help to highlight any usability issues. Modifications to the software, a choice of different software, or changes to team processes may need to be considered at this point to find the best fit between the usability of a system and the technical feature requirements of a platform.

Some key questions may be asked at this stage, which can form a part of usability testing: What did you like about software platform A compared to platform B? How long did it take you to book an appointment in software platform A compared to software platform B? How confident were you in using the platform? What did you find most difficult? What resources would you need to make using the platform easier? A cognitive walkthrough may also be useful for identifying the tasks, challenges, and nontypical behaviors occurring on a system that may act as barriers to or facilitators of ease of use [57-59].

At an organizational level, branding may also be an important consideration. If this is a relevant consideration, selecting white-label software (ie, purchasing a platform or license produced by a particular company but rebranded by the organization to make it appear to be their own platform) may be a priority. Alternatively, the organization may decide to embark on a software development process.

4.2. Integrate New Technology

The organization should not underestimate the time taken between software implementation and uptake by clinicians. Simply installing the software on clinicians' computers will not mean that clinicians will automatically be able to use it. Therefore, once the organization has selected a software provider, careful planning, communication, and training will be required to help expose clinicians to the platform and build confidence in its use. Once the technology has been selected, the organization will need to come up with a process to integrate this platform into its existing procedures. This may mean that the organization's current appointment scheduling, client monitoring, consent form distribution and collection, and client data or medical records systems need to be altered to accommodate the VCP platform and process. The process of integration will likely vary widely on the basis of an organization's current systems and the functions of the newly selected VCP software; therefore, an in-depth discussion of technology integration is not offered here. For an in-depth discussion of technology integration, organizations are recommended to refer to Pfeiffer [50].

4.3. Develop Videoconferencing Psychotherapy Guidelines

The introduction of VCP will likely require new policies or amendments to existing policies and procedures within the organization. This will require careful planning. In addition to establishing any changes to workflow, training requirements, and responsibilities of existing (or new) staff, the organization will need to consider policies involving informed consent for VCP and crisis management procedures. We encourage organizations to follow the recommendations put forth by Luxton et al [60]. Shore et al [17] outline several areas that will need to be considered when developing policy and operating procedures, such as roles, responsibilities, communication avenues and emergency procedures, agreements for training, and evaluation processes.

4.4. Develop Other Resources

Other resources, such as training materials and facilities (eg, clinical rooms), are essential for VCP. Once procured, all equipment and procedures should be rigorously tested to ensure that the platform works successfully before any implementation attempt. The workflow should also be tested to ensure that the entire system (from clerical staff scheduling an appointment to the clinician concluding a session) is working.

Organizing resources for clients should be another consideration in any implementation strategy. Access to all the required technology for the clients, including a good internet connection, is needed for VCP. This may be a critical issue because of the geographical dispersion of clients in the case of large organizations, which may affect the quality of internet services and the quality of the VCP. Organizations should consider having local rural sites, for example, a room in a medical center, which are accessible and equipped with all the required software and facilities for a client to engage with VCP. Such an arrangement would also address safety concerns for at-risk clients.

Reducing the burden on the client in terms of cost, and learning how to use the VCP technology, may encourage more individuals to take up this service, and this should be an important consideration in any VCP implementation attempt. Therefore, it is recommended that organizations have an employee available to clients to help facilitate the initial VCP appointment, perhaps also introducing the client to the VCP platform. In addition, the organization may consider developing instructional resources (eg, video demonstrations and PDF manuals) to assist clients setting up and preparing for VCP.

4.5. Provide Education and Training

Although VCP attempts to emulate the in-person experience as closely as possible, clinical staff will need to develop new skills that are required to successfully engage in VCP. Therefore, the organization must offer training and support to the clinicians around the provision of VCP services.

First, clinicians will need to be trained on how to navigate the technology. This training will provide an opportunity for the clinicians to become familiar with the VCP technology, procedures, and logistics of using the new modality. In particular, special VCP processes may be needed for booking appointments, distributing handouts, establishing client rapport, monitoring client comfort during sessions, and troubleshooting. These processes have been reported as barriers to delivering VCP in previous research [61]. Experiential learning (eg, role play) may be particularly useful here.

Training around supporting high-risk clients is also very important. Inadequate training of clinicians was identified as a key barrier in previous implementation strategies [22,25]. Even in in-person therapy, some clinicians have reported concerns around using trauma-focused treatments, because of fears of retraumatization and increased dropout [62]. Therefore, it is understandable that clinicians may hold reservations about using such approaches with VCP, despite studies demonstrating VCP to be safe and effective when using interventions, such as cognitive behavioral therapy and Prolonged Exposure for posttraumatic stress disorder populations [63,64]. However, Tuerk et al [63] did note that clients with more severe symptoms, such as high levels of hypervigilance, may be more difficult to treat with VCP. Training and identification of safe and effective approaches that can be used with VCP for such clients is therefore of paramount importance. Organizations may consider excluding clients entirely from receiving VCP when cognitive capacity, previous history of violence, or self-harm suggest that this is necessary. This is particularly necessary when geographic distance to the nearest medical facility and the lack of a local support system are of concern [17].

The goal of this training and education should be to alleviate several concerns clinicians hold around the effectiveness of VCP and any safety issues, allowing them to develop skills for working with complex mental illnesses, such as posttraumatic stress disorder, including risk management skills. The education and support of key clinical staff should be ongoing. This will lead to an increase in confidence and ultimately an increase in uptake. Organizations are encouraged to consult recent training and education guidelines from the ATA [17,18].

Delivery of this training could be a combination of both Web-based and in-person learning. A combination may facilitate buy-in and, at the same time, reduce cost and required resources. Organizations may consider developing a Web-based resource dedicated to VCP. Such a resource would provide staff with a centralized portal to access core and supplementary training materials and support (eg, a discussion board to engage with peers), as well as other relevant resources (eg, quick reference VCP pdf manuals). Having an accessible, single point of contact for follow-up support (eg, a telehealth coordinator or VCP champion) is also advised.

Ultimately, the organization should aim to keep training as comprehensive but as brief as possible. As discussed earlier, there may be some resistance to implementation from clinicians because of workloads. Clinicians will not want to spend any more time than is absolutely necessary to become proficient in using VCP. Organizations should therefore aim to keep training brief and to the point.

Finally, training will not be limited to clinicians. Clerical staff will also need to be trained in how to execute any new or modified tasks that have resulted from the introduction of the VCP service offering (eg, scheduling appointments, emailing instructional resources, and obtaining consent from clients).

Phase 5: Pilot Implementation

Once all the groundwork has been completed, establishing a sufficient base and framework for VCP implementation, phase 4 may commence. This phase has been broken up into the following 5 steps: pilot site implementation, process evaluation, provide ongoing training and support, recruit and engage more clinicians and clients, and demonstrate meaningful use. As with any pilot evaluation, these steps are likely to take between 6 and 12 months (depending on organizational capacity). As demonstrated in Figure 1 and explained below, the pilot phase also provides a critical opportunity to exit or reevaluate the implementation approach before significant time and finances are invested.

5.1. Pilot Site Implementation

It is recommended that the implementation process commence at 1 site [10,50]. This will be advantageous in identifying barriers and developing strategies to help overcome difficulties as they arise. Informed by the first 4 phases in this model, the development of an effective and uncomplicated strategy for the initial site will facilitate VCP implementation organization wide. For increased control, the organization may consider restricting this pilot to a limited number of clinicians and clients and for a fixed period of time [50]. In addition, the type of therapy and client might also be restricted during this initial pilot phase to those that are best suited to VCP. For example, managing high-risk clients via VCP may be a daunting prospect for clinicians. By removing such clients from the initial pilot, clinicians can focus on becoming accustomed to the modality.

In a further effort to ensure the pilot is a success, it will be important to ensure that participation is voluntary. Only clinicians and clients who want to engage in VCP should participate in the initial pilot. This should improve the likelihood of success, as the clinicians and clients will have a vested interest in making things work (and will be more persistent if barriers are encountered).

Once VCP has been successfully implemented at the pilot site, implementation can then occur at additional sites (one at a time).

5.2. Initial Process-Focused Evaluation

To ensure that the implementation plan is optimized, an evaluation should be simultaneously conducted on the basis of the plan developed in Step 3.1 (Implementation Plan). This initial evaluation will likely focus on process evaluation and potentially some preliminary examination of outcomes. With a small number of clients seen at this stage, it may not be possible to collect meaningful outcome data. However, quantitative data can be captured on feasibility and acceptability, using indices such as client uptake, numbers of sessions attended per client, nonattendance rates, dropout, out-of-session time spent per client, and client ratings of satisfaction. Alongside this, it will be useful to set up recording procedures for capturing data on the frequency of technology problems encountered, as well as any adverse events. Data collection and storage methods should be tested before implementation.

Qualitative data (via interviews) should also be collected at this time, Interian et al [22] provide an example interview schedule. The feedback collected from key stakeholders (eg, clients, clinicians, leaders, clerical, and IT staff) will assist in identifying challenges and barriers to VCP implementation. It is likely that those interviewed may offer solutions to overcome any difficulties experienced in the future.

Taken together, data collected for the process evaluation will allow the organization to identify strengths and weaknesses in the implementation plan. The results should inform any modifications required to the implementation plan and any decisions to modify or acquire additional resources, training materials, and policies. These decisions may already be defined (Step 3.4 Define Exit and Reevaluation Points). The results of the process evaluation and any changes made should then be communicated to all key stakeholders. Organizations may consider conducting seminars directed to its service providers, summarizing the initial implementation effort and the lessons learned.

It is likely that the pilot site implementation will cycle through several brief single-site iterations to integrate the findings of the process evaluation. As outlined in Step 3.4 (Define Exit and Reevaluation Points), the decision threshold for moving forward from a single-site pilot should be defined as a part of the implementation and evaluation plan, as well as thresholds for reevaluating and returning to earlier steps.

5.3. Provide Ongoing Support and Training for Clinicians and Staff

As identified in earlier stages, training and support for clinicians, as well as the wider team, is fundamental in overcoming implementation barriers and therefore critical to any implementation attempt. This support and training should be ongoing, addressing concerns as they arise and facilitated by the on-site champion. Clinicians will have needs in staying up to date with evolving VCP technology, research findings, and policies [17], which may need to be factored into training and clinician workload allocations.

At this time, the organization may wish to consider launching a mentoring program to help promote VCP, recruit clinicians and clients, and assist with the sharing of best practices. This has been found to be helpful for establishing newly implemented service offerings in geographically dispersed organizations [65].

5.4. Encourage and Recruit More Clinicians and Clients

Communication about the VCP implementation is critical for confirming the need for VCP and for disseminating best practices for VCP. This communication should be directed to clients and clinicians, with a view to encouraging additional clinicians to obtain VCP training. Again, this step will likely involve local champions promoting VCP.

Drawing on a greater pool of experiences and knowledge will help identify barriers and methods to overcome problems. The local champion may need to organize information and training sessions to facilitate recruitment of clinicians or promotional flyers to help recruit more clients.

5.5 Demonstrate Meaningful Use

As explained in Step 3.2 (Process Evaluation Plan), conducting a process-focused evaluation may introduce variables to service delivery that would ultimately not form a part of daily practice. With this consideration in mind, a period of meaningful use at the pilot site may be beneficial. This provides both staff and clients with the opportunity to engage with the VCP system, as it is intended to be used at scale.

Phase 6: Full Implementation

The next step is to implement the VCP service organization wide. This final phase involves 3 further steps; implement VCP organization wide, ongoing process evaluation, and, finally, outcomes evaluation.

6.1. Implement Organization Wide

Once phases 1 to 5 have been successfully completed, implementation of VCP on a wider scale may be considered. It is presumed that several challenges will have been addressed and a successful model of VCP established to help with this transition. It is recommended that the rollout should be a slow process to ensure participating sites are not rushed into the introduction of VCP and ensure they have sufficient time to organize their staff, training, and resources.

Education at site level should be thorough, and ongoing support should be available to clinicians from software suppliers and IT staff. Site-based VCP teams will need to be organized, and a local champion at each site is required to help facilitate communication, ongoing training, and problem solving. Organizations may also consider relocating willing staff from the initial pilot site to the next site, temporarily, to assist with implementation.

6.2. Large-Scale Evaluation

Using the plans developed in phase 3, the organization can now set out to evaluate the implementation and impact of VCP. The process evaluation should involve feedback from the key stakeholders, such as the clients, clinicians, and managerial staff to ensure their needs are being met and that a high standard of service delivery is maintained. This evaluation will also address any remaining problems or deficiencies.

Once organization-wide implementation is established, there may be sufficient data to examine the impact of VCP. Ideally, processes for data collection should integrate seamlessly into current clinical practice; however, the additional work involved with collecting consent, measures, and questionnaires, as well as collection of feedback from their clients to provide data for the outcomes evaluation, may make clinicians hesitant to participate in an evaluation. Methods for reducing this workload therefore need to be explored. Electronic consent processes may be helpful [17,66]. Having a dedicated external evaluation team with appropriate skills is an important consideration for an outcome evaluation. Employing an external team to perform the evaluation can help the organization to focus on service delivery, and this is especially useful for those organizations that may not have the capacity to conduct rigorous evaluations. Having an external evaluation team that is independent of the delivery of VCP has been found to be effective [27,37]. The team should be identified early in the implementation initiative to help develop the implementation and evaluation plan that is discussed in phase 3. This will ensure that those responsible for the evaluation can collect the necessary data to properly evaluate the service. Organizations are advised to refer to established guidelines for commissioning and executing evaluations [67-69].

6.3 Improve Quality

Once implemented, the steps in this model can be revisited to conduct targeted quality assessment and evaluation. For example, many software products may come to the end of their lifecycle as operating systems, and consumer preferences and organizational needs change. Returning to phases 1 to 4 may assist organizations in the transition to new technologies, with limited disruption to the workforce. Alternatively, regular scheduling of evaluation activities in phases 3 to 6 may assist with ongoing quality control. Therefore, the model presented here is not only applicable to initial implementation but can also be used postimplementation to assist organizations to modify or transition components of their established VCP service.

Discussion

Principal Findings

We have developed and described an integrative implementation model for VCP in large organizational settings in the public sector. A strength of this model is how it draws on multiple fields of research across mental health, IT, and organizational psychology to overcome the limitations of previous models and frameworks used in VCP implementation projects (see Multimedia Appendix 1). Organizations and researchers looking to implement VCP via this model are encouraged to use the VCP Implementation Checklist (see Multimedia Appendix 2).

The search strategy used to identify papers in our review of the VCP literature was not systematic, meaning our search was potentially biased and the quality of studies cited left unassessed; this is a limitation of our paper. Future research should consider a more systematic review of the literature to provide a more detailed assessment of the barriers, facilitators, and lessons learned from VCP implementation studies. In addition, this model highlights the need for additional research to be done regarding implementation of VCP into large organizations that do not target veterans. The model developed in this paper draws heavily on the experience of implementing VCP in the VA. Although this represents a large and geographically disperse organization, some of the challenges may be specific to veteran and military contexts and therefore may not translate to all organizational environments. It is therefore expected that this model will continue to evolve as researchers and organizations apply the model and report evaluation findings in nonmilitary environments.

Conclusions

The time and resources required to successfully implement VCP in large organizational settings, which are often geographically dispersed, are likely to be extensive and should not be underestimated. It is expected that the entire process may take several years to successfully complete, but the provision of mental health support via the internet has a critical role to play in reaching vulnerable individuals with limited access to such care. The ability of this modality to overcome barriers faced by clients cannot be ignored. It is hoped that the prescribed model will be useful for researchers and organizations to help guide and optimize VCP implementation efforts in the public sector in the future.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Staged approach for videoconferencing psychotherapy implementation.
[DOCX File , 22 KB - mental_v7i1e14996_app1.docx]

Multimedia Appendix 2
Videoconferencing psychotherapy implementation checklist.
[DOCX File , 22 KB - mental_v7i1e14996_app2.docx]

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Abbreviations

APA: American Psychological Association
ATA: American Telemedicine Association
HIPAA: Health Insurance Portability and Accountability Act
IT: information technology
PARIHS: Promoting Action of Research Implementation in Health Services
VA: Veterans' Affairs
VCP: videoconferencing psychotherapy

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Original Paper

Smartphone Monitoring of Participants’ Engagement With Home Practice During Mindfulness-Based Stress Reduction: Observational Study

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Abstract

Background: Standardized mindfulness training courses involve significant at-home assignments of meditation practice. Participants’ self-reported completion of these assignments has been correlated with treatment outcomes, but self-reported data are often incomplete and potentially biased. In addition, mindfulness teachers typically suggest that participants set aside a regular practice time, preferably in the morning, but the extent to which participants do this has not been empirically examined.

Objective: This study aimed to analyze patterns of participant engagement with home practice in a mindfulness-based stress reduction course.

Methods: We used a novel smartphone app to provide 25 participants with access to their daily practice assignments during the 8-week course. We analyzed data collected through our smartphone app to determine usage and listening patterns and performed analyses of the regularity and frequency of participant behavior.

Results: We found that participants listened to a median of 3 of the 6 practice sessions per week, and they did not typically set aside a regular daily practice time. Across weekdays, participants practiced most frequently in the morning, but there was considerable variation in participants’ practice start times. On weekends, the peak practice time was in the evening.

Conclusions: We suggest that it is feasible to integrate a smartphone-monitoring approach into existing mindfulness interventions. High-frequency smartphone monitoring can provide insights into how and when participants complete their homework, information that is important in supporting treatment engagement.

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KEYWORDS
mindfulness; adherence; smartphone monitoring; meditation practice; habit formation

Introduction

“Home Practice” in Mindfulness Training Programs

Mindfulness training programs have become extraordinarily popular in the last two decades [1]. The most rigorously evaluated of these programs are mindfulness-based stress reduction (MBSR) and mindfulness-based cognitive therapy (MBCT). MBSR and, its derivative, MBCT are manualized interventions. They follow a standardized syllabus, involving 20 to 26 hours of formal mindfulness training during 8 weekly group classes (1.5-2.5 hours/class), 1 all-day (6 hour) class, and home practice of mindfulness (about 45 min per day, 6 days per week). Home practices include the body scan (typically a lying down meditation, focused on sensations in the body), yoga, and sitting meditations supported by audio guides. The time commitment required from participants is substantial, but there is now a growing evidence base for these 2 interventions in improving mental health outcomes [2,3].

Home practice, one of the core components of MBSR and MBCT, is thought to be critical for learning but can also be challenging for participants to complete [4]. A recent meta-analysis of 48 studies found that participants report completing around 30 min of home practice a day on average, somewhat less than the recommended 45 min [5]. The extent to which participants report completing this practice was also correlated with treatment outcome (but the precise temporal precedence of practice, and related changes in outcome, has not been established). Although the average practice time was 30 min, there was also considerable variability across participants: some reported doing even more than the assigned amounts and other participants completed relatively little (eg, in one study, participants completed only one-fourth of assigned practices, see also a systematic review by Lloyd et al [6]). Given that these courses are used to treat mental health difficulties, and that practice completion is plausibly related to outcomes, a better understanding of participant engagement with practice is required.

Self-Reports, Missing Data, and the Timing of Practice

Two recent systematic reviews on home practice in MBCT and MBSR reported that nearly all studies to date have relied on self-report, retrospective, paper-based measures to monitor formal home practice. The problems with retrospective self-report are numerous and include memory lapses, socially desirable responding, and inaccurate recall, as well as loss of paper diaries [7]. These problems may be compounded where participants face mental health difficulties, which is often the case in mindfulness-based interventions. The few instances where technology-based recording methods have been used still required participants' manual input. For instance, one study used an electronic device (logger) to track the length of their home practice [8]. Another study asked participants to log home practice via a web-based portal [9].

Several recent studies have used technology-based methods, such as smartphone app usage data, or Web portals to record participants' practice time (a measure of the use of audio guides for practice) during mindfulness training. However, these studies have delivered their own mindfulness training courses rather than using the 2 standardized formats, MBSR or MBCT. Often, these training courses do not include a face-to-face group and have no human teacher, relying instead on automated and self-guided stand-alone programs that differ substantially from standardized formats. For instance, one study using a mindfulness app with patients with cancer assigned just 15 min of home practice to participants, substantially less than the 45 min assigned in MBCT or MBSR [10]. Just over half of the patients continued to use the mindfulness app consistently until week 10, completing a median number of exercises of 4 at week 1, to a median of 2 at week 10. Another study used an iPad app to record listening time during a 6-week mindfulness course, again with reduced home practice requirements [11]. Participants listened to around 23 min per day according to the app, with a drop to 16 min per day after the end of the 6-week course.

There is a clear gap in the implementation of automated recording methods for the courses for which the most clinical evidence has accrued, MBSR and MBCT. It is important that we understand participants' practice behaviors during these specific courses, which are now widely delivered in many countries. Indeed, one recent article argued that mobile technology will be crucial in solving some of the major methodological challenges in mindfulness research [12]. These challenges include how to measure participants' engagement with mindfulness practice rigorously, over the long-term, and with larger samples.

Although there are proponents of mobile technology for delivering mindfulness training, there has also been considerable concern that the technology itself may be disruptive to attentional capacities (for review, see [13]). For example, high-frequency digital media use has been associated with the emergence of new attention-deficit symptoms in a large longitudinal study [14]. As mindfulness training targets attentional capacities, there may be reasonable concerns as to the acceptability of a smartphone app, when smartphones are frequently viewed as a source of attention disruption [15]. Furthermore, nearly one-fifth of Americans (N=3511, 18%) report that technology use is a *very* or *somewhat* significant source of stress [16]. For individuals selecting to attend an MBSR course, prescribing technology use as part of the program may be incompatible with their reasons for participating (stress reduction).

Another key issue in MBSR and MBCT relates to the practical guidance given to course participants around the timing of their practice. It is often recommended that students dedicate *a specific time and particular place to practice* and that students might *wake up earlier and devote that time to practice* [17]. Such recommendations are consistent with numerous studies of health behavior change and theoretical models of habit formation (for review, see [18]), which emphasize the importance of repeating behaviors in consistent contexts. However, existing studies have not recorded or assessed when and how regularly MBSR and MBCT course participants practice. This information is of fundamental importance to both teachers and students in how they approach the assigned home practices, which can be challenging to complete.

To address this, we developed a smartphone app to provide participants with a convenient means to access their home practice guides during an MBSR course, while simultaneously recording their listening times. Smartphone-based tracking provides a means to better understand how and when people carried out their assigned home practice. By removing the requirement for participants to fill in paper diaries, we aimed to obtain more detailed measures of practice completion, with reduced demands on participants. In this exploratory study, we aimed to examine participant practice behavior during an 8-week MBSR program. We used a custom-developed app [19] that was designed to provide a simple user experience that did not conflict with any of the principles underpinning MBSR (eg, evaluating practice time as good or bad). We aimed to assess the number of practice sessions participants completed, the time of day participants practiced at, and the consistency of practice time.

Methods

Participants

We recruited participants from an MBSR course scheduled to run at the Danish Center for Mindfulness. Participants were invited to a face-to-face information session before the start of the course to decide if they would take part. Participants self-selected to attend this course and paid a fee (€467) and did not receive any compensation for taking part in this study. A total of 30 participants were initially registered on the course (women=21 and men=9).

All participants who consented to participate were provided with a smartphone (Motorola G5). The phones were preloaded with the custom-built Android app that contained the class teacher's own mindfulness practice guides. Participants were asked to use this phone to access their guides and not as a replacement personal phone. Qualtrics online software was used to collect participants' demographic and health-related information before the start of the MBSR course, midway through the course, and at the end of the course.

Participants were informed that their practice time data would not be shared with the teacher and would only be stored anonymously for research purposes. All participants provided written informed consent to take part. The study was conducted in accordance with the local Danish legal guidelines. There was no requirement for a formal ethical committee review because participants' treatment was not affected by participation in the study. Participants were already signed up to participate in the MBSR course before consenting to take part in this study. The study was registered with the Danish Data Protection Agency (AU-2016-051-000001).

Datasets from 25 participants were collected (4 women and 1 man not included from the original course). One participant changed to a different course time, 3 deleted the app before returning the smartphone to the research team, and 1 accessed their guides via alternate means (downloading MP3 files). All participants were Danish speakers. In all, 2 reported being on sick leave from work during the MBSR course. Most of the participants reported high levels of education (Table 1), and the average age was 49.3 (SD 11.5) years.

Table 1. Participant demographic information (N=25).

Demographic variable	Value, n (%)
Gender	
Male	9 (36)
Female	16 (64)
Living situation	
Alone	1 (4)
Living with partner	21 (84)
With children under 18 years	11 (44)
Education	
Apprentice or vocational courses	3 (12)
Medium long higher education (3-4 years at university level; eg, Bachelors)	8 (32)
Further higher education (>4 years at university level; eg, Masters)	12 (48)
Other education	2 (8)
Occupation	
Employed	21 (84)
Unemployed	1 (4)
Retired	2 (8)
Other	1 (4)

Mindfulness-Based Stress Reduction Class

A teacher who had a doctoral degree in psychology and was certified by the Center for Mindfulness in Medicine, Health Care, and Society, United States, taught the face-to-face MBSR class. The MBSR class was delivered as recommended in 2.5-hour weekly group sessions over 8 weeks with a 7-hour silent retreat day and 45 min of formal daily homework 6 days per week [20]. For classes 1 and 2, the formal home practice is called the body scan that focuses on nonjudgemental awareness to sensations in the body. From classes 3 and 4, participants are asked to alternate between the body scan and yoga practice, with yoga emphasizing mindful movement, through a series of gentle stretches. From class 5, participants are assigned sitting mediation practice, focusing on awareness of the breath, and yoga practice. From class 6, participants are asked to alternate the body scan practice with yoga practice. From class 7, participants are asked to practice on their own, without any specific recording, although participants can use the audio guides if they wish. The final class (class 8) emphasizes *making the practice your own* and using the recordings if desired. Participants on average attended 7.1 of the 8 classes (SD 1).

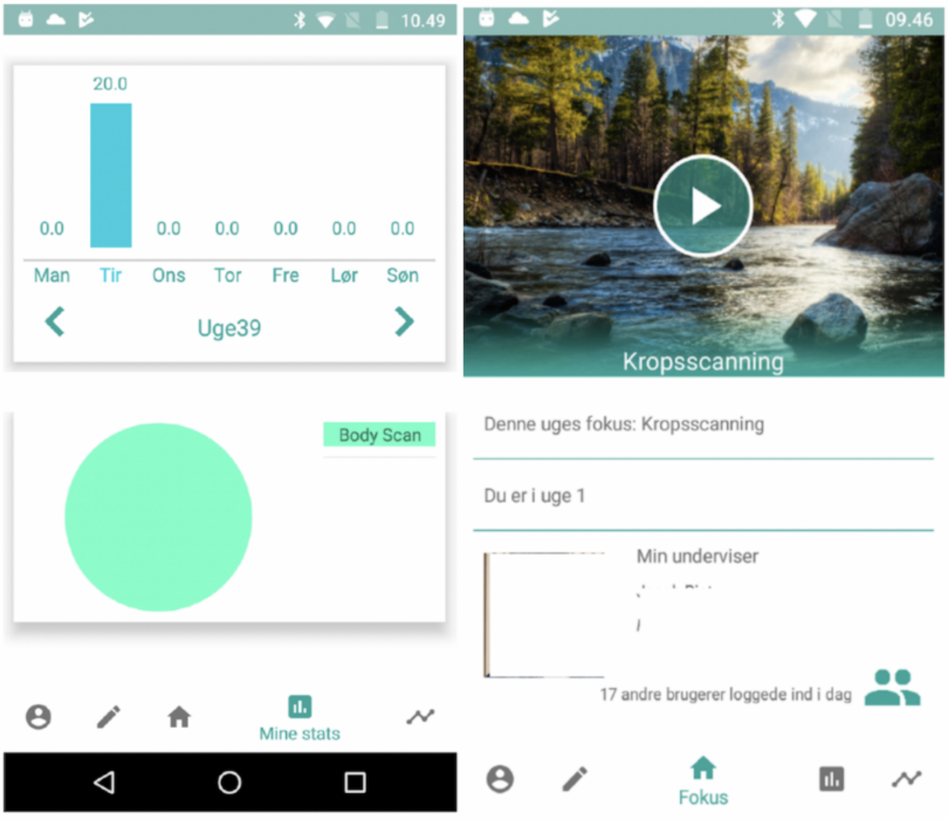
Smartphone App Design

We designed an Android smartphone app to present participants with home practice guides (body scan, seated meditation, and yoga) and to record the amount of home practice sessions that participants completed. The app was designed via a user-centered process, using focus group discussions with both mindfulness teachers and former students. The focus groups and the subsequent analysis followed and an experience-centered design approach, which was designed to *invite participants to creatively express something about themselves, their values, their relationships, and the ways they make sense of experience* [21]. The design process is reported in detail elsewhere [19]. In summary, the app was designed to include the teachers' own specific practice guides, rather than guides from another teacher. The app also included features such as reminders to practice, a way of recording students' motivation for participating in the course, and a diary.

The basic features of the finalized app were similar to those present in the Oxford mindfulness-based cognitive therapy app (Oxford MBCT). Specifically, students could select a guide, play and pause, and dim the screen. Participants could access visualizations of practice times (in minutes) from previous practice sessions using simple bar charts. These visualizations were designed to ensure that they did not provide any evaluation of the *correctness* of participants' practice behavior. There was no comparison of participant behavior against the assigned practice amounts, simply a graphical illustration of the participant's own behavior. The app also had a simple diary function, where participants could note anything important that occurred during their practice.

There were several features unique to our app. Although other apps have used mindfulness guides from well-known teachers (as in the Oxford MBCT app), we used guides prepared by the teacher who participants met in weekly face-to-face sessions. We presented these audio guides, along with a picture of the teacher. We also included a feature to allow participants to see how many others from their course logged into the app that day. The overall aim was to create a simple interface for participants that required minimal explanation or support from the research team. We wanted participants to be able to access their guides in a convenient manner and designed the app such that all other features were optional (such as, looking at their practice graphs, see Figure 1, or using the diary).

Figure 1. Screenshots from the app interface, illustrating the practice time visualizations (left) and the main screen with access to practice guides (right).



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Statistical Analysis

The metrics of interest were the frequency with which participants accessed the practice guides, the length of time spent listening to each of those guides, and the time of day at which those sessions were accessed. We analyzed participants' data from 9 consecutive weeks, rather than the typical 7 from the MBSR course. This was because there were 2 national holidays that fell during the standard 8-week course (holidays occurred on class 4 and class 6). We focused our analyses on our first 8 weeks of data, which represented the portion of the course where participants were assigned specific practices. In the last week, the participants were encouraged to practice without an audio guide, as per the MBSR course manual.

Analyzing the time participants spent listening to the practice guides, we calculated the sum of minutes logged for the full day. This was to account for instances where participants logged in and did a proportion of their practice and logged in again later. Furthermore, the app did not automatically stop the audio file playing when the participant closed it. We set the maximum practice time per day to 60 min because the home practice guides were 45 min long, and because 60 min was the upper limit of self-reported home practice found in a recent meta-analysis [5]. We also repeated our analyses with the maximum practice time per day set to a more conservative 45 min, and this did not change the pattern of results obtained.

We examined the regularity of participants' practice time using a number of strategies. First, we examined within-participant patterns of regularity, using the standard deviation from each participant's mean practice start time. Second, we calculated a stability index for participants' practice start time and used this to examine changes across the 8-week course. This method was adapted from a well-established measure in sleep timing research, where the regularity of sleep patterns is important (the Sleep Timing Questionnaire [22]). We assigned each participant's standard deviation in practice times (for each week) as a number on a 9-point scale, with higher numbers indicating greater irregularity, based on the following intervals: 1: 0 to 1 hours, 2: 1 to 2 hours, 3: 2 to 3 hours, 4: 3 to 4 hours, 5: 4 to 5 hours, 6: 5 to 6 hours, 7: 6 to 7 hours, 8: 7 to 8 hours , 9: >8 hours.

Self-Report Measures

The Symptom Check List-5 (SCL-5), a short form of the Hopkins Symptom Check List-90, was used to measure symptoms of anxiety and depression [23]. The Perceived Stress Scale (PSS-10) was used to measure the degree to which an individual perceived life as unpredictable, uncontrollable, and overloading during the previous month [24]. Table 1 provides all available data from the participant demographic questionnaires.

Results

Table 2 presents all available data from participants' PSS scores. Most participants self-reported experiencing moderate (52.2%) to high (13%) levels of stress (using cutoffs reported, for instance, in [25]).

Table 2. Self-report questionnaires: Perceived Stress Scale and Symptom Check List scores at baseline, midintervention, and postintervention.

Questionnaire	Preintervention		Midintervention		Postintervention	
	n (%)	Mean (SD)	n (%)	Mean (SD)	n (%)	Mean (SD)
Perceived Stress Scale-10	22 (100)	17.5 (6.9)	21 (100)	15.1 (5.3)	12 (100)	13.9 (6.1)
Low perceived stress (0-13)	7 (31.8)	—[a]	8 (38.1)	—	7 (58.3)	—
Moderate perceived stress (14-26)	12 (54.5)	—	12 (54.5)	—	5 (41.7)	—
High perceived stress (27-40)	3 (13.6)	—	1 (4.5)	—	0 (0)	—
Symptom Check List-5	22 (100)	10.9 (3.3)	22 (100)	10.7 (3.3)	17 (100)	9.2 (2.3)

[a] Not applicable.

App Usage: Practice Listening Time

Participants completed practice sessions a median of 3 times per week from week 3 onward (see Figure 2). In the weeks with assigned home practices (weeks 1-8), participants (n=25) listened to a mean of 3.1 (SD 0.9) practice sessions weekly. In week 1, the mean number of sessions was 4.36 (SD 1.9). By week 3, participants' mean number of sessions was around 3.48 (SD 2.5). In the final week, where participants did not have an assigned audio recording (the guidelines suggest doing practice without any guide, but participants could use an audio guide if they wished), 9 participants listened to recordings a total of 26 times. This suggests that course participants used the app throughout the course, even when they were not assigned a specific session that required app use.

On average, participants listened to 123.15 (SD 40.86) min of audio recordings per week across weeks 1 to 8. In the first week of the program, the average listening time was 187.05 min. A simple linear regression was used to examine trends in listening time over the 8 weeks with assigned practice. As the course progressed, participants spent significantly less time listening to the recordings (F_{1314}=83.5; R^2=0.06; beta=–0.35; *P*<.001). The most frequently accessed recording was the *body scan*. In total, participants played this for 443 sessions out of a total number of 793 sessions. Next most frequently accessed was the *yoga* recording that was played 183 times, and the *sitting meditation* was played 167 times.

When Did Participants Practice?

The most common start time for a practice session was in the morning (between midnight and midday), in which 34.4% of sessions occurred (see Figure 2), and in the evening, in which another third (35.14%) of the sessions were completed. The afternoon (between midday and 17.00) was the second least popular time, with 29.7% of the listening times occurring in this time window; 0.7% of the sessions were done during night time. There were 2 distinct peaks in practice times, around 08:30 am and 7:45 pm on weekdays. At weekends there was a peak at around 7:00 pm (see Figure 3).

Figure 2. Box plot showing participants' number of listening sessions recorded over the weeks of the course with assigned practice (week 1-8). The median listening time for each week is represented by black dots in each box, and the broken lines represent the minimum and maximum quantiles.

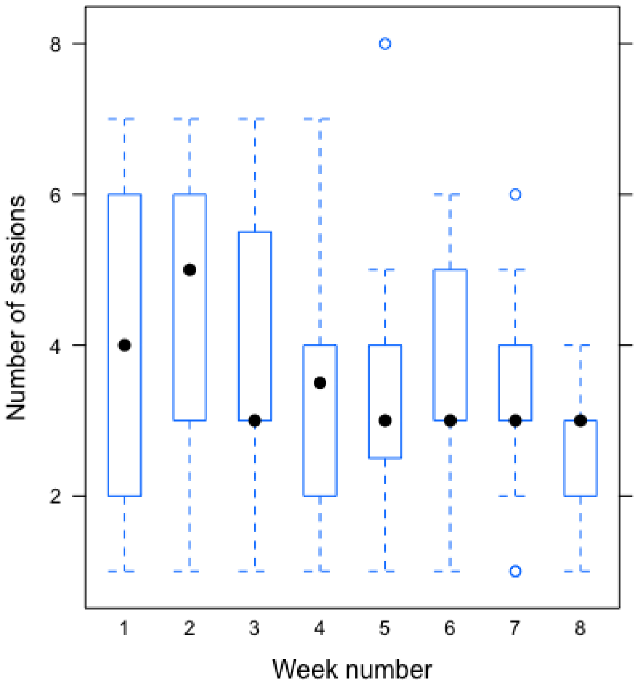
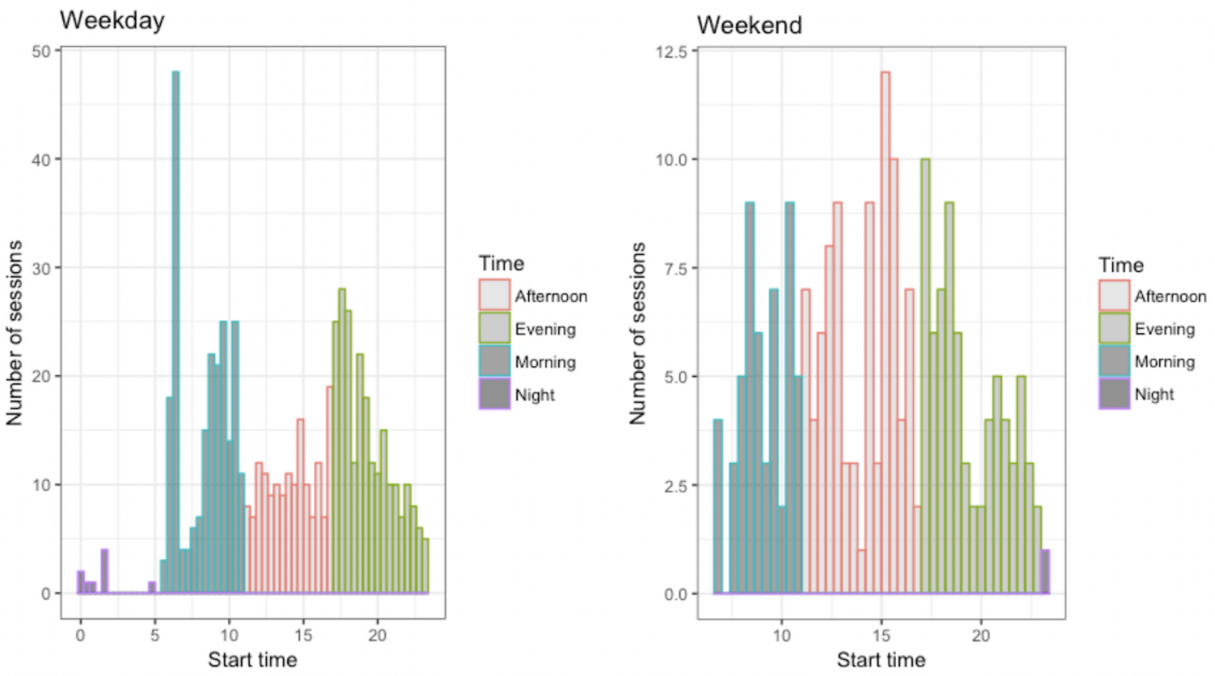


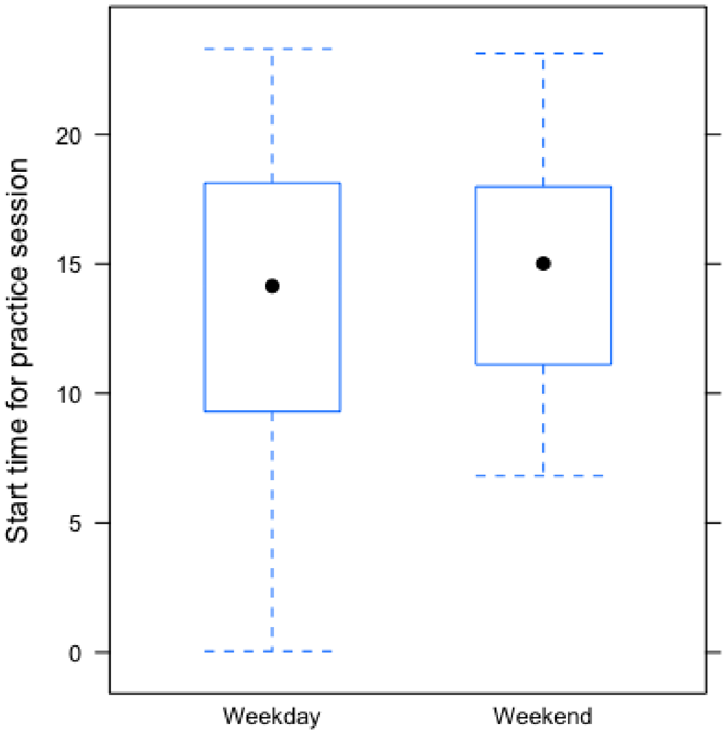
Figure 3. Histogram showing the start times and number of sessions completed in the morning, afternoon, and evenings, across weekdays and weekends.



Practice Time Regularity

Across the 25 participants, there was significant variability in the regularity of their listening times. Some practiced at similar times every day, whereas others did not. For instance, one participant had an overall standard deviation in practice time of 0.43 (corresponding to 25.8 min), and another had an overall practice time standard deviation of 8.17 (corresponding to approximately 8 hours and 10 min). The average standard deviation in listening time was SD 4.0 corresponding to 4 hours. Overall across all participants, there was more variability in start times across the weekdays (SD 5.21) compared with the weekends (SD 4.24, see Figure 4). Looking at within-participant variability, for weekdays, the average SD in start time was 3.78, and for weekends, it was 3.33.

Figure 4. Box plot illustrating the variability in participants' practice start times on weekdays and weekends. The whiskers represent the minimum and maximum quartile, showing the size of variability in practice start times, which was greater during weekdays. The median starting time is indicated by black dots.



The majority of participants (68%) had an overall stability index that corresponded to 3, 4, or 5 (between 2 and 5 hours of variation in practice start time). We also repeated this analysis looking specifically at weekdays, excluding weekends. The mean stability score for weekdays was 3.6 (SD 2.5), whereas for the full week it was 3.8 (SD 2.4), a difference that was statistically significant (t_{125}=–1.96; *P*=.05). Participants therefore were slightly more regular in their weekday start times, as compared with the full week.

A linear regression showed no significant changes in participants' stability indices over the full course (F_{132}=0.09; R^2=0.007; beta=0.02; *P*=.80). This indicates that participants did not adopt a more regular practice time as the course progressed. A linear regression model showed no significant relationship between the calculated stability index for practice time and the amount of listening time participants completed (F_{21}=1.3; R^2=0.01; beta=–87.36; *P*=.28) This suggests that, for the small sample included here, having a more regular practice time was not associated with greater practice listening time.

Discussion

Principal Findings

We used a smartphone app to monitor participants' engagement with the home practice assignments within a standard format 8-week MBSR course. From this smartphone listening time data, we found wide variability in how much participants listened to their home practice guides, with a median of 3 sessions per week recorded, compared with the assigned 6 sessions. This number of sessions is similar to findings from previous studies using paper-based recording methods (eg, [5]). Notably, we were able to assess, for the first time, when and how regularly (ie, day-to-day variation) participants carried out their home assignments. Participants most frequently practiced in the morning, and in the early evening during the weekdays, and in the afternoon at weekends. Analysis of the time patterns suggested that participants were generally not setting aside a regular practice time, even when examining weekdays only.

Number of Sessions and Timing of Practice

Our data indicate that participants used the app throughout the course, in a manner that is in line with previous paper-based monitoring studies. In fact, participants frequently used the app even during the week when they were told they could practice without it (week 7 in the MBSR program). This suggests that the smartphone-monitoring approach presented here is feasible to implement, and this allowed us to analyze key features of participants' practice.

Participants' median number of listening sessions was roughly comparable with findings of previous studies of standard format MBSR and MBCT courses (see systematic reviews by [5,6]). The wide variation in the number of practice sessions that people completed was also in line with general findings in the field. We also found that participants gradually listened to fewer guides as the course progressed. This is in line with other studies showing that participants report practicing the most in the early weeks of the course, with a gradual drop-off as the course proceeds [26]. The most commonly accessed guide was the body scan meditation that was logical, given that the body scan is the most frequently assigned activity in the program (ie, it is the only assigned practice for the first 2 weeks, and for other weeks, participants are asked to alternate between the body scan and other practices [27]).

Our key finding was that the most frequent practice time during weekdays was in the morning, where there was a clear peak in participants' listening frequency. This suggests that many participants are setting some morning time to practice, in line with the seminal recommendations from Williams et al [17]. However, on weekends, this pattern shifted, and participants' peak listening time was in the early evening. We performed analyses on the regularity of participants' practice which indicated that, on average, participants did not stick to a consistent practice time from day to day. We found that participants were slightly more consistent in their start times across weekdays, compared with the full week, but there was still considerable weekday start time variability (approximately 3 hours).

This information on timing and regularity of practice is of clear importance to teachers and may be used to better support participants' home practice. Research on habit formation suggests that consistency, choosing the same time and place for the target behavior, is of particular importance (eg, [28]). For mindfulness practice, teachers may helpfully address this, particularly for students who are having difficulty completing their home practice. Whether it is important that participants practice at the same time during the weekdays and weekends is an open question for future research. Students might be guided to reflect on their own routines, or lack thereof, to establish and maintain a mindfulness practice *habit*. Research on completion of other health-related behaviors suggests that weekends can be more problematic than weekdays. For instance, studies on medication-taking behavior show that weekend doses are more likely to be missed than weekday doses (eg, [29]), and having a medication routine (taking at the same time each day across the week) is associated with better adherence (eg, [30]).

We did not find evidence for an association practice regularity and overall practice time in our statistical analysis; this may have been because our sample size was small. The aim of this exploratory work was not to establish that such effects exist, rather to systematically measure home practice in a standard format MBSR course using a smartphone-based automated method. In particular, we were able to examine features of practice, timing, and regularity, which paper-based methodologies have not monitored. We believe this information is of interest to mindfulness teachers and students because we know that it is more difficult to repeatedly engage in a behavior if it is not part of a daily routine. This smartphone-monitoring approach, if scaled up, would allow us to test the importance of regular practice time for practice engagement and its association with outcomes.

Limitations of the Smartphone-Monitoring Approach and This Study

There were several limitations to this approach. First, we assumed that participants used the smartphone app as their only means of listening to their mindfulness practice guides. This may not have been the case. There is an abundance of MP3 files available for free online (along with other popular apps, such as Headspace), and participants could have practiced with these, even though they are not strictly the assigned practices. It is also possible that participants did silent practices and not the assigned practices. Second, it is possible that participants pressed play on the guide within the smartphone app but did not actually listen to the guides. For instance, one participant in our user-centered design group suggested that she might *cheat* by pressing play on the recording and leave the phone while she engaged in other tasks [19]. We cannot exclude such a possibility.

Third, we had poor completion rates for the final follow-up mental health questionnaires, and we did not obtain a measure of state (eg, the Toronto Mindfulness Scale [31] or trait mindfulness (eg, the Five-Facet Mindfulness Questionnaire [32]) which would have been of interest. Poor questionnaire completion rates have been reported in similar self-paying participant samples [33]. Furthermore, 3 participants deleted the app before returning the smartphone to the research team. We took this as an indication that those individuals were opting out of participating in the study, in addition to the participant who chose to download MP3 files instead of using the app. These participants did not communicate a reason for deleting the app, and we did not have a procedure in place to ask about this.

It may be that those participants were uncomfortable sharing data on their practice behavior with the research team. Opting out of sharing data may be because of nonadherence, as is often discussed in relation to missing data on medication adherence [34]. It may also be because some adults are less comfortable sharing data related to mental health issues, compared with other aspects of health [35]. Although we informed participants that their practice data would not be shared with the class teacher, we could also have added a data sharing option within the app. This could have served a dual function: allowing participants to share data with their teacher if they wished and reminding participants explicitly that they could choose not to do this. For a small subset of participants, smartphone recording of treatment engagement may be undesirable, and they may prefer to use more traditional means of accessing their practice guides.

Finally, we acknowledge that this is a small sample, and the self-selecting nature of the participant group limits the potential generalizability of the findings. Through their self-selection, we can assume that our participants here were motivated to practice mindfulness, perhaps more so than participants who do not seek out this specific course, as now sometimes occurs in health care settings. This is important because there is evidence that patient preference for treatment can impact treatment outcome [36]. Indeed, there is evidence that baseline differences between adults before training can predict engagement with practice [37]. This suggests that there may be characteristics that differentiate those attracted to mindfulness from the general population [1].

Strengths of the Study

The majority of participants used the app regularly across the course, although there was wide variation in the actual number of listening sessions recorded. Overall, this suggests that smartphone-based access to mindfulness guides is feasible and acceptable to most participants. There are several advantages to this approach: it offers a convenient and universal means for participants to access their home practice guides. Participants otherwise use a variety of MP3 players and desktop computers to access these and typically do not record their home practice completion.

Furthermore, we suggest that this approach will reduce the burden to the teacher of having to manually collect 25 to 30 home practice diary sheets from class participants. There have been numerous calls for better monitoring of participants' *at-home* treatment engagement [5,6]. In fact, although recording of home practice completion is common in research studies, it is not widely carried out in community settings. In fact, the Danish Centre for Mindfulness, where we conducted this study, did not use practice recording forms, despite being a research-oriented center, because of the additional administrative task in doing so.

Smartphone recordings also reduce the burden on participants of having to fill in additional paperwork. This is important because it is often the case that a self-selecting and self-paying population (which is typical for MBSR) show low participation rates when asked to fill in questionnaires on their experiences during the MBSR program [33].

Although mindfulness-based apps are incredibly popular, the actual use of app-based monitoring with clinical populations, and in standardized mindfulness-based interventions, is limited. Mindfulness apps have been explored predominantly in academic research in nonstandardized and often brief training formats [38,39]. We bridge this gap, using a smartphone app in a real-world context, to support adults in a community setting who had already signed up to attend an MBSR course. This type of population is of clear interest and arguably distinct from those who already engage with health-related technology (adults who are health conscious and who want to quantify progress; [40]).

Avenues for Future Work

The issue of the practice *dosage* in mindfulness training is among the most important practical questions [12] yet has received little research attention. By *scaling* this app for use with larger samples of participants, and multiple teachers, it will be possible to address outstanding questions in the field. For example, is it more effective to practice in multiple, brief sessions in a given day, or in one longer session, as currently recommend? Is it more sustainable to practice in the morning, and can this be maintained beyond an 8-week program? and Should participants be advised to practice at similar times across weekdays and weekends? At present, we do not know the answers to these questions.

The app-based approach presented here offers a feasible route to longer-term assessment of participants' mindfulness practice behavior. This is of interest, because the majority of studies report on participants' practice only during the 8 weeks of the MBSR or MBCT program [6], and the limited available evidence of within-participant changes suggests that higher practice engagement 2 to 6 months after training predicts lower levels of subsequent stress [41]. By relying on methods that require less concerted efforts from participants and researchers, it is likely that we can collect larger, more representative datasets on postintervention practice.

Although we focus on mindfulness-based interventions, there are numerous other evidence-based treatments where homework is a central component, such as Cognitive Behavioral Therapy (CBT). In CBT, patients are asked to record thoughts and emotions, plan activities, or track mood, and compliance with these homework exercises has been correlated with treatment outcomes (meta-analysis; [42]). It has been clearly argued elsewhere that well-designed apps might helpfully support patients in their CBT homework completion [43,44]. We further propose that the systematic recording of homework completion, its timing and consistency as we achieved here for MBSR, may also be of value. Studies examining the homework completion and CBT treatment outcome association have relied on paper-based self-reports for the most part [42], as for MBCT and MBSR. Smartphone monitoring offers a number of clear advantages in terms of convenience and the potential for automaticity.

We used our app to collect time-based metrics only, but smartphones provide a number of methods for measuring physiological signals relevant to mindfulness practice. Recent work has, for example, correlated heart rate measured with contact photoplethysmography (contact of fingertip to built-in camera) and electrocardiograms and reported reasonable accuracy [45]. Breathing rate has also been measured using noncontact video recordings of chest and abdominal motions, correlated with respiration belts measures, again with reasonable accuracy [46]. These physiological signal measurements might be integrated into smartphone monitoring of at-home mindfulness practice and would provide new ways to link laboratory-based experiments of practice with real-world measurements. Finally, our app did not directly assess participants' user experience *in vivo* (eg, via an inbuilt feature*)*, and in-depth qualitative examinations of individuals' experiences will be of clear importance for future development of the app.

Conclusions

The 2 standardized mindfulness training courses with the most substantial body of clinical evidence, MBSR and MBCT, involve significant *at-home* assignments of formal mindfulness practice. Participants' self-reported completion of formal home practice is associated with treatment outcomes, but self-reports are considered to be methodologically problematic. Furthermore, it is often recommended that course participants set aside a regular practice time, preferably in the morning. However, the extent to which participants do this has not been systematically examined. In this study, we used a novel smartphone app to provide participants with access to the daily at-home practice exercises during MBSR. We found that participants listened to a median of 3 of the 6 assigned practice sessions per week over the 8-week course. During weekdays, participants practiced most frequently in the morning, but there was considerably variation in participants' practice start times. During the weekend, the peak practice time was in the evening. Overall the data suggested that participants did not set aside a regular daily practice time. We suggest that it is feasible to integrate a smartphone-monitoring approach into an existing, well-established mindfulness intervention, and this can provide valuable insights into participant behavior. This information may be helpful to both teachers, students, and researchers in establishing the most effective means to support treatment engagement.

Acknowledgments

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Conflicts of Interest

LOF is the director of Danish Center for Mindfulness. LOF receives payments for presentations, workshops, and teacher training related to MBSR and donates payments to the Danish Center for Mindfulness. JP has received honoraria or fees for courses on mindfulness or mindfulness-based stress reduction (MBSR). All authors declare no other conflicts.

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Abbreviations

CBT: cognitive behavioral therapy
MBCT: mindfulness-based cognitive therapy
MBSR: mindfulness-based stress reduction
PSS: Perceived Stress Scale
SCL: Symptom Check List

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Review

Functionality of Top-Rated Mobile Apps for Depression: Systematic Search and Evaluation

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Abstract

Background: In the last decade, there has been a proliferation of mobile apps claiming to support the needs of people living with depression. However, it is unclear what functionality is actually provided by apps for depression, or for whom they are intended.

Objective: This paper aimed to explore the key features of top-rated apps for depression, including descriptive characteristics, functionality, and ethical concerns, to better inform the design of apps for depression.

Methods: We reviewed top-rated iPhone OS (iOS) and Android mobile apps for depression retrieved from app marketplaces in spring 2019. We applied a systematic analysis to review the selected apps, for which data were gathered from the 2 marketplaces and through direct use of the apps. We report an in-depth analysis of app functionality, namely, screening, tracking, and provision of interventions. Of the initially identified 482 apps, 29 apps met the criteria for inclusion in this review. Apps were included if they remained accessible at the moment of evaluation, were offered in mental health–relevant categories, received a review score greater than 4.0 out of 5.0 by more than 100 reviewers, and had depression as a primary target.

Results: The analysis revealed that a majority of apps specify the evidence base for their intervention (18/29, 62%), whereas a smaller proportion describes receiving clinical input into their design (12/29, 41%). All the selected apps are rated as suitable for children and adolescents on the marketplace, but 83% (24/29) do not provide a privacy policy consistent with their rating. The findings also show that most apps provide multiple functions. The most commonly implemented functions include provision of interventions (24/29, 83%) either as a digitalized therapeutic intervention or as support for mood expression; tracking (19/29, 66%) of moods, thoughts, or behaviors for supporting the intervention; and screening (9/29, 31%) to inform the decision to use the app and its intervention. Some apps include overtly negative content.

Conclusions: Currently available top-ranked apps for depression on the major marketplaces provide diverse functionality to benefit users across a range of age groups; however, guidelines and frameworks are still needed to ensure users' privacy and safety while using them. Suggestions include clearly defining the age of the target population and explicit disclosure of the sharing of users' sensitive data with third parties. In addition, we found an opportunity for apps to better leverage digital affordances for mitigating harm, for personalizing interventions, and for tracking multimodal content. The study further demonstrated the need to consider potential risks while using depression apps, including the use of nonvalidated screening tools, tracking negative moods or thinking patterns, and exposing users to negative emotional expression content.

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KEYWORDS

mobile apps; depression; review; ethics; mHealth

Introduction

Background

Depression is a major affective disorder with significant socioeconomic cost [1], affecting over 300 million people worldwide [2] across the life span [3]. However, access to treatment is problematic [4] given the acknowledged barriers such as high treatment cost, time constraints [4], geographical location [5], and stigma [4-7]. With over 90% worldwide penetration [8], mobile phones have significant potential to scale up the provision of interventions targeting depression [9]. They are especially useful to reach users who do not normally seek professional support, such as adolescents [10]. Prior work has already indicated a high user acceptance and effectiveness of mobile-delivered interventions for depression [11,12]. The number of mobile apps available on marketplaces offering treatment for depression has also been growing rapidly [9,13].

The apps available on mobile phone marketplaces provide access to a range of interventions targeting depression [14-16], which people can select and download to fit their needs [17]. Yet, users acting independently can only select apps based on information that is available at the point of download, ie, popularity, user ratings, or app descriptions provided on the marketplaces. Evidence for supporting assessment of the quality of an app, ie, structured description of its main features, evidence-based functionality, and potential risks, is not reflected in user ratings of apps [18,19]. Additionally, marketplaces do not require app developers to provide such information [20,21]. As a result, concerns have been raised regarding the lack of an evidence base for mental health apps [15,19,22] and poor regulation of the major mobile marketplaces [23-25] hosting them. Prior work [26] has also suggested the importance of having controlled clinical trials to determine the efficacy of new therapeutic treatments. In this newly established field of mobile health (mHealth) apps, most apps claim to be informed by evidence-based treatments rather than presenting rigorous evaluations of the app itself.

Besides efficacy, understanding patients (eg, their characteristics, needs, and behaviors) is also key for improving the uptake of apps [26,27]. Most human-computer interaction (HCI) studies on understanding [28-30] or supporting depression have focused on designing and evaluating mobile technologies in research contexts rather than marketplaces [31-33]. Scholarly work has also called for the evaluation of commercial apps for depression to support the effective development of the rapidly growing market of commercial apps [10,13,15]. However, such evaluations tend to focus in isolation on specific aspects such as ethics [34] and safety [35] or on specific interventions such as cognitive behavior therapy (CBT) or acceptance and commitment therapy (ACT) [10,19]. Moreover, previous evaluations tend to analyze app information from marketplaces without the actual experience of using the apps [15].

Objectives

This paper addresses these limitations by focusing on a broader range of interventions and functionality of the top-rated apps for depression. Thus, we focused on the following research questions:

1. Which are the key functionalities of the top-rated apps for depression available on iPhone OS (iOS) and Android marketplaces?
2. Is this functionality described and delivered in a way that supports user privacy and safety?

Methods

Overview

This paper focuses on apps selected in spring 2019 from 2 major marketplaces, iOS and Android, whose analysis triangulates (1) reviewing app ratings on marketplaces to identify the top-rated apps for depression, (2) reviewing app descriptions on marketplaces, and (3) experimental evaluation through author interaction with the apps as expert HCI researchers [36,37].

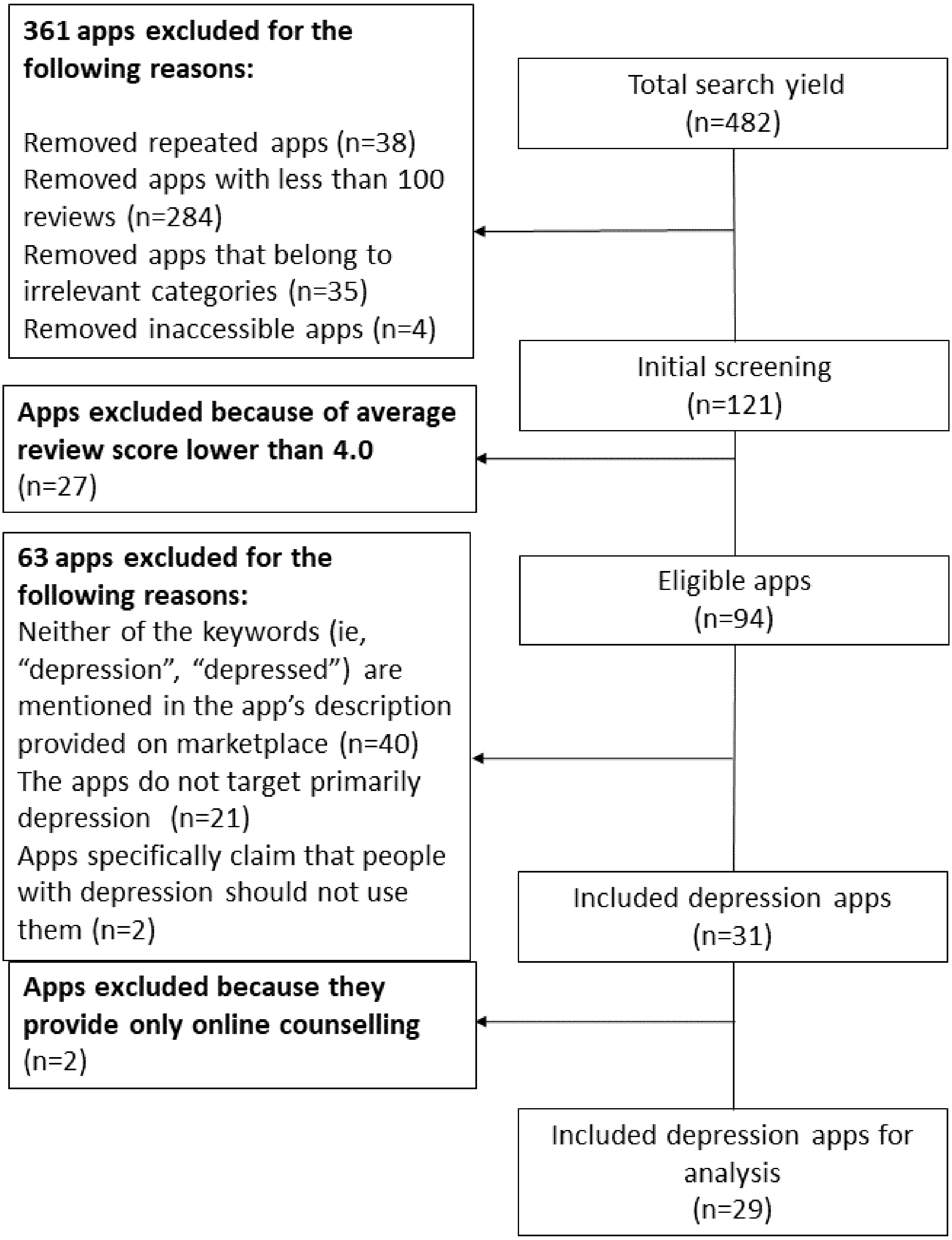
App Selection

We now describe the selection process (Figure 1). The apps were initially identified through the 2 keywords “depression” and “depressed” entered into App Crawler and Google Play search engines. A script was used [38] to extract all the apps shown in the search results. The script automatically downloaded information for each app from its marketplace, including name, category, marketplace description, price, review score, and number of reviewers. This resulted in 482 apps, and after removing duplicates, 444 apps were included in the later selection.

The strategy for app selection outlined in Figure 1 aimed to include top-rated publicly available apps targeting primarily depression. From the initially identified 444 apps, we excluded those that (1) had less than 100 reviews; (2) were inaccessible at the time of selection; (3) belonged to irrelevant marketplace categories such as social, casual, business, news, or book; and (4) had average user review scores lower than 4.0 (out of 5.0). The application of these criteria on the initial set of 444 apps resulted in 94 apps for consideration.

From these apps, we further excluded those that did not focus primarily on depression by employing the following criteria: (1) the words “depression” or “depressed” do not appear in the app’s title or marketplace description of the app, (2) the primary target is not depression (eg, yoga tracker), and (3) their marketplace description mentions that people with depression should not use the app. These criteria led to 31 apps, from which we further excluded 2 more apps as their functionality was limited to the provision of therapy sessions to be purchased in-app. The remaining 29 apps were analyzed in this review (see Multimedia Appendix 1).

Figure 1. App extraction progress.



Data Extraction

Descriptive characteristics of the apps were extracted from the information provided on the marketplace. These included *category*, *costs*, *target audience*, whether they claimed to be *evidence-based* (including explicit scientific underpinning and clinical input), and data supporting analysis of ethical aspects such as the *privacy policy*.

To extract data on app functionality, between June and October 2019, 2 rounds of experimental evaluation [36,37] were used in which the authors as HCI experts interacted with the apps using both Android and iPhone mobile devices (ie, Samsung tablet and Xiaomi phone for Android apps and iPhone for iOS apps). The entire set of apps was evaluated by 2 authors (CQ and CD), and 21% (6/29) of the apps were evaluated by all authors. The coding scheme was iteratively revised until agreement was reached among all the coders. The coding process was hybrid, integrating both deductive and inductive coding. Informed by prior work on the classification of mHealth apps [14], the deductive codes consisted of 3 main types of functionality of depression apps: screening, tracking, and provision of interventions (Table 1). The inductive coding [39] allowed the identification of specific subcodes under each of the main functionality described above. For instance, the screening function was broken down into subcodes such as symptom monitoring, self-diagnosis, and basis for personalization.

Table 1. Main codes and subcodes from functionality's evaluation.

Functionality type and subtype	Definitions
Screening	
Monitoring symptoms	The screening function is provided for monitoring depression symptoms during intervention
Self-diagnosis	The screening function is provided for self-assessment of depression
Basis for personalization	The screening function is provided as a basis for personalized intervention
Tracking	
Tracking thought patterns	The tracking function supports the tracking of thought patterns
Tracking mood patterns	The tracking function supports the tracking of users' mood patterns
Tracking behavior as the intervention progresses	The tracking function is provided for monitoring progress in following the intervention, including users' adherence to the intervention
Tracking depression symptoms	The tracking function is provided for monitoring symptoms
Intervention	
Thought diaries	The intervention is provided to help users identify and challenge their negative thinking patterns
Psychoeducation	The intervention is provided as psychoeducational content
Mindfulness	The intervention is provided to help users improve mindfulness
Behavioral techniques	The intervention is provided to motivate and guide users to perform positive behaviors
Mood expression	The intervention is provided for users to express their emotions
Other	The intervention is provided as emotional regulation strategies other than mindfulness

Results

Overview

The description of findings is organized into 3 parts. The first outlines a broader picture focusing on descriptive app characteristics (eg, categorization). The second part covers ethical considerations. The third part looks in more depth into specific functionality such as screening, tracking, and provision of interventions.

Descriptive Characteristics

This section describes the characteristics of the selected apps, for example, the main categories under which depression apps are classified on marketplaces, their target audience, costs, evidence base, medical disclaimer, and whether involving of clinicians' guidance while using the apps.

Categorization

The 29 apps reviewed in this study belong to 3 categories used to describe apps on the marketplaces. The most popular category is health and fitness (18/29, 62% apps), followed by lifestyle (4/29, 14% apps) and medical (7/29, 24% apps).

Targeted Audience (Age Group)

An important finding is that app marketplaces rate all apps as suitable for nonadult users (Multimedia Appendix 2). Most of the selected apps were classified as being suitable for children from preschool age: 76% (22/29) of apps were rated for those older than 3 years, 3% (1/29) for those older than 4 years, 7% (2/29) for those older than 12 years, 3% (1/29) for those older than 16 years, and 10% (3/29) with parental guidance.

However, only 41% (12/29) of the apps provide a privacy policy intended to protect children's data. Half of these privacy policies (7/12, 58%) claim to restrict users to a specific age group, albeit this approach is inconsistent with the app's age rating on the marketplace. For instance, one app (A8, see app_ID in Multimedia Appendix 2) states in its privacy policy that the app does not provide services to users who are younger than 18 years; in contrast, it is rated on the marketplace as Pan European Game Information (PEGI) 3. This may be because of a mismatch between age rating definitions oriented around the inclusion of material such as violent content, and health care apps that should have age restrictions because of the personal and sensitive nature of the content, with associated risk for harm.

In addition, all the apps apply the same design across all ages, and we did not find any customization for users who are children, such as involving in-app interactions to allow parents to collaborate or monitor their children while using the app [40].

Targeted Audience (Clinical Nosology)

All included apps claim to target users with depression. Most of the apps (20/29, 69%) represent *depression* as a lack of well-being (eg, feeling stressed or having low mood). Less than one-fifth of the apps (5/29, 17%) actually represent depression as a mental disorder, whereas only 1 app (A18) employs Patient Health Questionnaire-9 (PHQ-9) [41] to assess the severity of symptoms. Another 14% (4/29) of apps do not claim to target depression as a disorder, yet employ validated tools for assessing users' depressive symptoms. Furthermore, none of the apps claims to target users with a specific level of severity (ie, mild, moderate, or severe depression).

Costs

An important finding is that although most of the apps (28/29, 97%) are free to download, at least some of their costs are covered either directly or indirectly by users (Multimedia Appendix 2). The direct costs consist of explicit charges for more advanced features, whereas indirect costs relate to users' forced consumption of in-app advertisements. In-app purchase was offered by 66% (19/29) of the apps, mostly as a subscription priced between US $3.99 to US $29.99 per month, or as paid online therapy sessions (US $35/hourly session over call, video, or chat, A11). Advertisements were provided by 34% (10/29) of apps, which raises privacy concerns. Of the apps with advertisements, 80% (8/10) stated specifically in their privacy policies that users' information, captured for instance through cookies, would be collected and shared with third parties, including advertisers or analytics providers. Only 1 app that offered advertisements claimed that users' data would not be collected or shared (A29), whereas another app (A7) did not provide a privacy policy in English. Only 17% (5/29) of apps that are free to download neither request in-app purchase nor provide advertisement. Only 1 app requires purchase (for US $4.99) before downloading.

Evidence Base

Developers of 62% (18/29) of the apps have specified a scientific underpinning for their app design, whereas another 38% (11/29) do not make such a claim (Multimedia Appendix 3). Almost half of the apps (14/29, 48%) claim to be designed based on validated psychological treatments (eg, CBT, ACT, dialectical behavior therapy, and mindfulness). The remaining 14% (4/29) are designed based on theories pertaining to gamification, hypnosis, and affirmations. However, only 7% (2/29) of the apps provide direct evidence in the form of peer-reviewed scholarly work on the efficacy of the app for reducing depression symptoms [42,43], whereas another 34% (10/29) of apps provide indirect evidence of efficacy of their underpinning theories without referencing any academic work. For instance, 8 apps (A3, A4, A5, A15, A16, A17, A18, and A28) are promoted as evidence-based therapeutic tools by claims that their design is grounded on evidence-based treatments (ie, CBT). In addition, 41% (12/29) are described as being designed with input from clinicians (eg, psychologists, psychiatrists, and therapists), whereas 59% (17/29) do not mention the involvement of mental health professionals in their design.

Medical Disclaimer

A medical disclaimer is presented in 66% (19/29) of the apps, outlining that the app is not a replacement for clinical treatment (Multimedia Appendix 3). However, 11 out of these 19 apps (11/19, 58%) only present this disclaimer in their terms of use policy, which is difficult to find and unlikely to be read by users. Another 35% (10/29) of apps do not provide any disclaimer on either marketplace or app's website. No app presented itself as an alternative to clinical treatment (ie, drug treatment or face-to-face psychotherapy).

Clinical Involvement

All apps are designed to be used independently and do not require professional guidance while using them (Multimedia Appendix 3). In addition, 5 apps (5/29, 17%) provide opportunities to involve health experts while using the app. Of these, 2 apps support access to coaching and counseling sessions as an additional intervention for a price ranging from US $29.99 per month (A27) to US $35 per hour (A11). The other 3 apps allow users to share their in-app data (eg, health tracking report) with their health care providers (A16, A22, and A24).

Ethical Considerations

This section describes the ethical considerations raised while reviewing selected apps.

Negative Content

Aligned with the concerns raised by prior work that apps with poor design present an increased risk of potential harm [15,44], the results show that 2 out of 29 apps are categorized as so-called wallpaper apps. Such apps support people, "reflecting the true nature of the pain and loneliness in [your] heart […] give permission to feel the way you do" (A12). We found that these 2 apps include images or quotes capturing negative thinking (eg, "Do you ever get in those moods where you just don't feel like existing," A12). Surprisingly, these 2 apps with potentially disturbing content are rated as PEGI 3 (A12) or PEGI 12 (A6) on the marketplace, which indicates that the apps' content merely includes bad language. As prior studies [45,46] have indicated, adolescents' exposure to negative content may trigger negative behavior such as self-harm. Therefore, there is a clear need to explore safeguarding strategies for protecting vulnerable users such as those at risk of self-harm or suicide, especially given that these 2 apps are highly rated on the marketplace, ie, between 4.4 and 4.6 out of 5, and are subsequently more likely to be selected for use, adoption, or appropriation [47].

Safety

Strikingly, despite the increased vulnerability of people living with depression, 72% (21/29) of apps do not provide any information for handling or preventing the risk of suicide (Multimedia Appendix 4). Only 28% (8/29) of apps provide such information; in particular, most of these apps (5/8, 63%) provide information on accessing suicide prevention helplines, counseling websites, or support services, whereas 25% (2/8) provide information advising users to contact local emergency services if in critical risk of harm. In addition, 1 app (A18) assists users in creating a personalized safety plan for handling crises.

Functionality Review

We now discuss the functionality of reviewed apps such as screening, tracking, and providing interventions.

Screening

A total of 9 apps offer functionality to screen for depression; their features are summarized in Multimedia Appendix 5. Almost half of the apps that provide screening functionality (4/9, 44%) aim to assess changes in users' depression symptoms during engagement with the app-provided intervention. Interestingly, despite the acknowledged benefit of personalization to support adherence [48], most of these apps (3/4, 75%) provide predefined psychoeducation articles upon informing users of their screening result, rather than tailored information for addressing particular issues identified through screening. All 4 of these apps employ the PHQ-9, a validated screening tool. An interesting outcome in this context relates to the frequency of the screening. Although 2 apps supported periodic repeated measures of users' depression (ie, apps suggest or limit access to the screening tool only once in a fortnight), another 2 apps instead allowed on-demand momentary screening of users' depression (ie, users can access screening tools as frequently as they want with no instructions regarding an appropriate frequency).

In addition, 33% (3/9) of the apps provide stand-alone screening functionality for self-diagnosis purposes. Furthermore, 2 out of 3 apps classified into this category provide only screening functionality (A29 and A24), whereas another app (A16) also provides mood regulation strategies in addition to screening as its primary function. The first 2 apps (A29 and A24) do not use validated screening tools and do not provide direct in-app links to professional help upon informing users of the severity of their screening results. We found that the other app (A16) enables the potential benefits of screening while avoiding harm, as it provides support for both psychoeducation and for discussing the diagnosis and its implications with mHealth professionals [15,19]. In addition, the app (A16) provides screening as the main functionality through the use of International Classification of Diseases-10 [49], a validated screening tool, and in-app links to professional support. A16 also allows users to generate a report of the screening result to show to their own health care professionals.

The other apps (2/9, 22%) provide a screening function to inform the delivery of personalized app content. One app asks users to self-report their disorder and symptoms (A19), whereas another app uses a questionnaire as a screening tool (A11), although it provides neither the source of this questionnaire and information on its validity nor evidence for the personalization of intervention. This app offers in-app purchase of online therapy sessions; however, this is not integrated with users' progress through the intervention or their screening results.

Tracking

Out of the 29 apps, 19 apps offer functionality for tracking at least one aspect such as *thoughts*, *behaviors*, *moods*, or *depression symptoms* (Multimedia Appendix 6).

Apps that track multiple aspects serve different purposes; 89% (17/19) of these apps support tracking to assist the provision of personalized intervention, ie, tracking *thought* changes for providing materials to apply within the intervention or tracking users' *behavior* for visualizing their progress and adherence to the intervention. Furthermore, 37% (7/19) of the apps support *mood* tracking for revealing their triggers and patterns. Another 26% (5/19) of apps support tracking of *symptoms of depression* through frequent use of screening tools, and 1 of these 5 apps (A16) tracks aspects such as thought changes, mood, or physical condition (ie, appetite, sleep) over fortnightly periods to generate the screening result.

Thought tracking is supported by 74% (14/19) of the tracking apps, mostly combined with mood tracking on the same data entry. Good practices for improving usability have started to emerge, for instance, in the form of templates for guiding users through the tracking process (available in 11/14, 79% apps). There is also an opportunity to explore alternative modalities for mood tracking. From the selected apps, we found that text is the most commonly employed modality for recording thoughts (14/14, 100% apps) and moods (9/14, 64% apps). Other modalities such as emoticons are being used to record moods tagged with thoughts (4/9, 44%), and scales are being used to record mood intensity (1/9, 11%). Opportunities also arise for better representing the thought logs, for instance, introducing searching or filtering functionality. Currently, all 14 apps present thought logs directly to users in chronological order without the option of searching them.

Of the 42% (8/19) apps that track user *behavior* as progress through the intervention, 3 apps automatically log users' adherence to the proposed usage goals for app-delivered intervention (eg, minutes spent on app-delivered meditation), whereas 5 apps track user's achievement of positive behaviors suggested by the app (eg, socializing with friends and drinking water). Apps for the latter purpose mostly require users to log their achieved activity themselves, whereas 1 app allows automatic tracking (ie, step count, A13). In addition, only half of the progress-tracking apps (5/8, 63%) provide a summary visualization of intervention progress (2 apps provide a graphical summary, eg, A11 provides a calendar view). Another 3 apps provide a textual summary (eg, A17 displays the total number of minutes of meditation, without providing a record of each specific meditation). The other 38% (3/8) of apps provide direct access to textual logs with no summary.

In addition, 37% (7/19) of the apps support the understanding of *mood* patterns through visualizations. Such apps often track moods alongside their triggering factors (available in 4 apps) or physical conditions such as headache (available in 4 apps); the aim of the former is to understand the reasons for changes in mood, whereas the latter aims to reveal the impact of physical conditions on such changes. Despite the clear purpose of supporting understanding articulated by developers, the representation of logged data does not easily support the understanding of data patterns. Even though a graphical view of mood changes over time is provided by all 7 apps, most of them (4/7, 57%) provide it separately from the graphical view of other tracked factors (eg, A14, A28, and A11 provide a graphical view of mood changes within a period and a textual representation of mood triggering factors). Another 3 apps (3/7, 43%) offer an integrated representation of changes in physical condition with changes in mood, which may make it easier to understand relationships between the two.

Furthermore, 26% (5/19) of the apps automatically track screening results for *symptom* monitoring. Most of these apps (4/5) provide only a textual review of screening results, in chronological order. Only 1 app (A28) also provides a graphic visualization of changes in screening results.

Interventions

Overall, 5 types of interventions were identified in the analysis (see Multimedia Appendix 7), reflecting a mixture of elements from psychological interventions, including *thought diaries*, *psychoeducation*, *mindfulness*, *scheduling positive behaviors*, and *others*. A distinct group of apps aims to support *emotional expression* rather than a particular psychological intervention.

Thought diaries are a common intervention employed by one-third of the apps (9/24, 38%). This intervention borrows from traditional CBT practice by providing instructions for identifying negative thought patterns and for challenging distorted thoughts. One approach to tailoring interventions is to employ guidance for challenging real-time tracked thoughts or emotions. Most of these apps (7/9, 78%) provide thought diaries as tailored interventions consisting of guidance for identifying and selecting personal challenging thought patterns to guide the writing of reflective diaries. Another 2 apps provide a generic template to guide thought diaries, rather than adaptive or personalized guidance.

Apart from thought dairies, another set of 9 apps (9/24, 38%) provide specific *psychoeducation* as an intervention. Findings suggest that 44% (4/9) of such content is provided to specifically fit users' depression assessment, whereas 56% (5/9) is nonpersonalized, generic content.

Mindfulness [50] is another popular intervention (11/24, 46%) as most of the selected apps include meditation (9 apps), grounding techniques (1 app, A26), or breathing guides (1 app, A2). Furthermore, 4 apps suggest a frequency of use for the intervention, eg, 1 meditation session per day (A1), whereas the others do not specify a frequency of use. In addition, 2 apps provide adaptive interventions (ie, meditation guidance) triggered by users' input (eg, during users' conversation with artificial intelligence [AI]–based chatbot, A27 and A28).

In addition, 17% (4/24) of the apps delivered interventions for *scheduling positive behaviors* (or behavior activation). Aligned with prior work, personalization [19,29] is a good design principle for engaging users with app-delivered interventions. Overall, 3 apps offer tailored intervention materials by allowing users to enter positive behaviors that they wish to schedule (eg, A15, A18, and A21), and another app (A11) provides a personalized monthly plan based on the results of the users screening measures. Other valuable design choices supporting engagement include offering peer support [19] during the intervention (1 app, A21) or using gamification for providing daily intervention goals and rewards [51] for completed activities (2 apps, A11 and A21).

A final category of apps is those helping users to *express their emotions* associated with depression (5/24, 21), either by sharing posts in online support groups or by individually consuming art-based materials. Of the 2 apps providing peer-supported mood expression, only 1 provides links to a 24/7 suicide helpline. Both apps allow users to filter posts: 1 app (A23) allows users to set filter words (eg, "suicide") to hide posts including such words and safeguard themselves from such content, whereas another app (A19) filters materials (ie, posts in the community) automatically and only shows materials that relate to users' self-reported disorder and symptoms. Apps that fall in the latter category (3/5, 60%) provide art-based content for expressing depressive moods, eg, wallpaper pictures with emotional quotes. However, an important concern is that none of the wallpaper apps provide any scientific background or features to support access to mental health services for users at risk of suicide or self-harm. Most of the content of these 3 apps are negative, and only 1 of these apps also provides some positive content, being also the only app that offers users the possibility of personalizing the quotes.

Another 3 apps provide *other* types of emotion regulation strategies, including positive affirmations (1 app, A25) or hypnosis (2 apps, A10 and A20). Customization of intervention material is available in 1 app (A25), which allows users to create positive affirmations and to audio record them.

Discussion

Principal Findings

This paper indicates that the current top-ranked apps for depression provide various features to benefit users across different age groups. The potential of this newly established marketplace is promising, especially for reaching subgroups of users such as adolescents, who are less likely to seek professional support offline and thus could benefit from appropriately designed mHealth apps. For this purpose, we discuss the need and opportunity for regulating the marketplace to safeguard users and to ensure a positive impact from the use of apps.

We begin by considering the ethical principle of nonmaleficence [52] within the top-rated apps for depression. First, a clearer definition of age restrictions on the marketplace could better support users in general and younger users in particular to select age-appropriate apps. We found age to be handled insufficiently and inconsistently in current commercial apps, given that the age ratings on the marketplace generally indicate the maturity of app content rather than the targeted users for the app, and we also found that these ratings were generally inconsistent with information regarding the targeted age group. This risk is further heightened by the conditions within the reviewed apps' privacy policies including the sharing of users' data with third parties for commercial purposes.

A recent systematic review of HCI work on affective health technologies also identified potentially harmful aspects of tracking apps such as the provision of negative mood or thinking patterns with insufficient professional support, inadequate screening, and insufficiently founded diagnosis claims based on tracked data [30]. With respect to communicating negative content, we see apps supporting the consumption of publicly shared emotional expressions of depression generated by others (A6 and A12). We further advocate that developers should consider the presence of negative content when selecting an age rating on the marketplace, as consumption of such content may lead to harmful behavior among adolescent users.

In addition, this paper systematically reviewed and analyzed the apps' functionality. The result inspires recommendations to guide developers to further leverage digital affordances to mitigate harm, to deliver personalized depression treatments, and to track multimodal content. For instance, for apps that provide screening functionality, there may be a tendency to overclaim symptom screening informed by nonvalidated screening tools rather than using validated ones, eg, developers of A24 and A29 prominently state their apps' effectiveness in clinical practice on the marketplace but do not provide scientific validation for the screening tools employed. In addition, with regard to the increased vulnerability of depressed individuals, we find limited direct access to professional help when screening results are communicated to users. For instance, in general, 76% (22/29) apps do not provide immediate access to suicide prevention or online counseling helplines (Multimedia Appendix 3).

Safeguarding Users While Accessing and Consuming Negative Content

Risk of harm can be identified with respect to the viewing of strongly negative content from others within the emotional expression apps for depression. Our findings highlight strong ethical concerns around these apps. Although arguably beneficial for people creating it [53], such content might have a negative effect on those viewing it, especially given that depressed individuals have a tendency toward rumination [54]. We suggest that such apps should include safeguards for users viewing highly negative content. Moreover, developers of such apps could limit views of negative content, especially given that these 2 apps (A6 and A12) are also accessible to adolescent users, who are susceptible to engage in *problem* or *at-risk* behaviors [40]. One deployed strategy was to automatically cover negative keywords within app-provided content and to offer a pop-up window with free psychological counseling helpline every 3 times when users choose to reveal the hidden negative words (A23).

In addition, apps not specifically designed for children and adolescents, but with a child-friendly age rating on the marketplace, should consider introducing customizable designs for nonadult users. It has previously been suggested that providing support and treatment sessions with parents, teachers, and siblings should be seriously considered when administering treatment to children with depression [40]. Therefore, we suggest that designers of such apps should consider mechanisms to engage parental support or supervision while children or adolescents are using these apps.

An interesting issue with respect to apps supporting the tracking of mood and thought patterns is the unfiltered presentation of these data when predominantly negative content is being tracked. Apps tracking thoughts only provide access to tracking logs in chronological order, and this presents a 2-fold limitation. First, such visualizations can be browsed but not queried to retrieve a specific entry. Second, browsing such logs may trigger vivid recall when they capture negative content and may increase the risk of rumination [29].

Safeguarding Users While Selecting Age-Appropriate Apps and Sharing Private Data

The suggestions discussed in this section particularly target the developers of marketplaces hosting apps for depression. Previous findings suggested that the regulation of such apps regarding data privacy remains inadequate [25,32,35] and reported the prevalence of health-related apps selling users' data to third parties. Survey studies have also indicated that the general public is less inclined to share their health care data with technology companies [32]. The identified limitations of the privacy policies for the reviewed apps illustrate that these concerns can be better addressed; 24% (7/29) of the apps failed to provide any privacy policy in English or in a reliable source (Multimedia Appendix 2). In addition, aligned with prior studies [26,55], the current privacy policies may be difficult to comprehend by typical users. We, thus, call for developers to improve the readability of privacy policies and support the suggestion of making them easy to read at a sixth-grade reading level [26].

Another concern is protecting the privacy of users' health data and, in particular, the data of young people while using depression apps. First, more than half of these apps (24/29, 83%) fail to provide privacy policies that specify strategies to protect children's data (16/29, 55%). Second, our findings also show that although most of the apps are free to download, they normally come with in-app purchases for additional features or advertisements. Regarding advertisement, we found that 80% (8/10) of apps that use advertisements declare that they share users' data for commercial purposes.

All of the reviewed apps are rated as suitable for children and adolescents on the marketplace, whereas one-fifth (7/29, 24%) of the apps specifically claim to restrict access from young users. This finding demonstrates the need for developers of marketplaces that host depression apps to increase the transparency of their standards. For instance, Google specifies that [56] their age rating is not for describing the apps' target user group but rather for describing the minimum maturity level of content in apps such as violence, drugs, and profane language.

Surprisingly, however, no statement regarding data sharing or targeted users' age range could be found on the app descriptions in the marketplace to support users making an informed decision at the point of downloading the app. The age rating may be specifically misleading to parents when they are selecting age-appropriate apps for their children as developers only claim age restrictions in the privacy policy. We advocate a clearer definition and regulations for age rating of depression apps on marketplaces.

In addition, we argue that users should be informed upfront of the risk of having their sensitive data shared with third parties for commercial purposes. The prevalence of health-related apps selling users' data to third parties has been previously reported [25,35,57]. Thus, we argue for the responsibility on the marketplaces' developers to ensure consistency of privacy-related information in the app description on the marketplaces when compared with its privacy policy or to ensure that the privacy policy is included directly within the app.

Safeguarding Users While Screening for Depression

Prior studies [57] have reported the tendency of commercial depression apps to blur the line between depression as a lack of wellness or as a mental disorder, which aligns with our findings. In addition, none of the apps examined claim to target a specific level of depression severity. Although apps may potentially reach a wider range of users by following such a strategy, it may be more difficult to formulate appropriate safeguards for users whose depression leaves them with higher levels of vulnerability [57]. In addition, we found that most depression apps tend not to undergo a rigorous evaluation of their intervention components but instead rely on designing the app based on evidence-based theory [26]. Apps with insufficient evidence of efficacy present challenges as they may risk misinforming patients [57]. We advocate clear communication of the targeted user groups for mHealth apps and marketplace guidelines to match the required level of evidence for each app as well as the condition and risks of their specifically targeted user group.

App-based depression assessment is potentially valuable in supporting individuals with depression concerns to seek help and share their electronic health information with health professionals [15,26]. In addition, health data collected by users could support professionals' understanding of users' symptoms, which could support diagnosis and the delivery of clinical treatment. Despite these potential benefits, the top-rated depression apps reviewed seldom support this usage. Only 1 of 8 apps offered the option of generating reports of screening outcomes for sharing with mental health professionals.

Although PHQ-9 is the most used tool for depression screening, 3 out of 8 apps use nonvalidated screening tools, and information about screening tools and their scientific underpinning is seldom provided within app descriptions. We recommend that app developers use validated screening tools and provide basic information about the tools and their validity.

In addition, findings indicate that screening tools employing periodic repeated measures such as PHQ-9 [41] also tend to be used within apps during daily tracking. However, the latter may be better suited to more lightweight ecological momentary assessment measures [58] rather than depression diagnosis measures. We also found a few emerging practices addressing this concern by suggesting an appropriate frequency for screening or even limiting the frequency of access to screening tools (A16 and A28). Thus, we suggest that app developers decouple the use of periodically repeated measures such as PHQ-9 for the purpose of depression screening and the use of ecological momentary assessment for more frequent daily tracking of mood, thoughts, behavior patterns, and symptoms of depression [59].

Opportunity to Improve Apps for Depression by Leveraging Digital Affordances

An important challenge of mobile apps for depression is attrition [29,60]. Previous work suggested the value of personalization for improving users' engagement with apps [19,29,61] and the value of accessing social support [19] and involving concepts from gamification [51]. In the future, this may involve the provision of real-time adaptive personalization of intervention content to the tracked thoughts or emotions [59]. However, despite the potential of mobile technology to deliver personalization, apps supporting it are limited. Exceptions here include the use of AI chatbot conversational agents (A2 and A28) to respond in real time to users' currently recorded thoughts, instead of generic (not personalized) psychoeducational content. Personalization can also be extended to the schedule of activities within an app-delivered intervention. However, only 1 of the reviewed apps (A11) offered a personalized intervention plan based on users' screening results. There is an opportunity to better leverage digital affordances for personalization when designing apps for depression.

Findings also indicate that tracking within depression apps is focused on capturing users' mood patterns or thought patterns and their engagement with app-delivered interventions. However, these distinct types of tracked content are seldom available together in a single app. We argue for the value of simultaneously capturing both thinking and emotional content as these can support better encoding at the moment when an event occurs and better retrieval later [62,63]. We also suggest that integrating such tracked content with a record of progress through the intervention and completion of intervention activities could better allow users to understand the value of the app for their well-being. Such combined visualization could further support users' engagement and motivation to continue to use the app-delivered intervention.

Conclusions and Future Work

The rapid increase of mobile apps for reducing depression can benefit from a closer look and evaluation of the functionality such apps actually deliver and the potential ethical issues that they raise. From a systematic analysis of 29 top-rated depression apps on the major marketplaces, we suggest that developers of marketplaces should regulate depression apps to mitigate ethical risks, including missing, inadequate, or inconsistent privacy policies, ie, sharing data with third parties, child data protection, and safeguarding of vulnerable user groups. In addition, the analysis of app functionality provided new insights into opportunities for mitigating harm regarding the consumption of the negative content, unrestricted access by children (with related privacy concerns), and the provision of screening tools with less scientific validation.

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Conflicts of Interest

GD is a cofounder of SilverCloud Health, a provider of supported online treatment, and has a financial interest in the company.

Multimedia Appendix 1
List of selected apps.
[DOCX File , 17 KB - mental_v7i1e15321_app1.docx]

Multimedia Appendix 2
Assessment of targeted audience and costs.
[DOCX File , 27 KB - mental_v7i1e15321_app2.docx]

Multimedia Appendix 3
Assessment of apps' evidence base.
[DOCX File , 18 KB - mental_v7i1e15321_app3.docx]

Multimedia Appendix 4
Assessment of Safety design.
[DOCX File , 19 KB - mental_v7i1e15321_app4.docx]

Multimedia Appendix 5
Assessment of the screening functionality (9 apps).
[DOCX File , 21 KB - mental_v7i1e15321_app5.docx]

Multimedia Appendix 6
Assessment of the tracking functionality (19 apps).
[DOCX File , 22 KB - mental_v7i1e15321_app6.docx]

Multimedia Appendix 7
Assessment of the intervention functionality (24 apps).
[DOCX File , 23 KB - mental_v7i1e15321_app7.docx]

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Abbreviations

ACT: acceptance and commitment therapy
AI: artificial intelligence
CBT: cognitive behavior therapy
HCI: human-computer interaction
iOS: iPhone OS
mHealth: mobile health
PEGI: Pan European Game Information

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Original Paper

Exploring Mental Health Professionals’ Perspectives of Text-Based Online Counseling Effectiveness With Young People: Mixed Methods Pilot Study

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Abstract

Background: Population-based studies show that the risk of mental ill health is highest among young people aged 10 to 24 years, who are also the least likely to seek professional treatment because of a number of barriers. Electronic mental (e-mental) health services have been advocated as a method for decreasing these barriers for young people, among which text-based online counseling (TBOC) is a primary intervention used at many youth-oriented services. Although TBOC has shown promising results, its outcome variance is greater in comparison with other electronic interventions and adult user groups.

Objective: This pilot study aimed to explore and confirm e-mental health professional’s perspectives about various domains and themes related to young service users’ (YSUs) motivations for accessing TBOC services and factors related to higher and lower effectiveness on these modalities.

Methods: Participants were 9 e-mental health professionals who were interviewed individually and in focus groups using a semistructured interview. Thematic analysis of qualitative themes from interview transcripts was examined across the areas of YSU motivations for access and factors that increase and decrease TBOC effectiveness.

Results: A total of 4 domains and various subthemes were confirmed and identified to be related to YSUs’ characteristics, motivations for accessing TBOC, and moderators of service effectiveness: user characteristics (ie, prior negative help-seeking experience, mental health syndrome, limited social support, and perceived social difficulties), selection factors (ie, safety, avoidance motivation, accessibility, and expectation), and factors perceived to increase effectiveness (ie, general therapeutic benefits, positive service-modality factors, and persisting with counseling despite substantial benefit) and decrease effectiveness (ie, negative service-modality factors).

Conclusions: Participants perceived YSUs to have polarized expectations of TBOC effectiveness and be motivated by service accessibility and safety, in response to several help-seeking concerns. Factors increasing TBOC effectiveness were using text-based communication, the online counselor’s interpersonal skills and use of self-management and crisis-support strategies, and working with less complex presenting problems or facilitating access to more intensive support. Factors decreasing TBOC effectiveness were working with more complex problems owing to challenges with assessment, the slow pace of text communication, lack of nonverbal conversational cues, and environmental and connectivity issues. Other factors were using ineffective techniques (eg, poor goal setting, focusing, and postcounseling direction) that produced only short-term outcomes, poor timeliness in responding to service requests, rupture in rapport from managing service boundaries, and low YSU readiness and motivation.

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KEYWORDS

mental health; child health; adolescent health; distance counseling; mHealth; applied psychology; psychological processes

Introduction

Background

Over the past 2 decades, electronic mental (e-mental) health services have emerged as a promising avenue for intervention because of the advantages they have in accessibility, efficiency, and effectiveness over traditional service provision [1-7]. In particular, these services have been advocated for use in public health strategies for young people aged 10 to 24 years [6-10], who have the highest risk for developing emotional and mental health problems and are the least likely to seek professional treatment because of a number of help-seeking obstacles [11-18].

Online counseling is a common e-mental health intervention offered at youth helplines across the world [7,19] and is described by Barak and Grohol [20] as a "*mental health intervention between a patient [or a group of patients] and a therapist, using technology as the modality of communication*" (p. 157). Herein, text-based online counseling (TBOC) is a common typology that allows asynchronous (eg, email and forums) or synchronous (eg, Web chat) communication between young service users (YSUs) and online counselors. Although face-to-face counseling remains the preferred counseling modality for most YSUs [21-23], a growing number of YSUs are expressing a preference for online interventions [21,22].

Studies show that the most common factors influencing a YSU's selection of TBOC services are the heightened levels of safety associated with interface-related privacy, anonymity, control, and reduced nonverbal feedback from the online counselor; increased accessibility resulting from convenience, affordability, and ease of access; and polarized minimal-to-heightened expectations about the outcome of counseling sessions [24-32]. YSUs are observed to access TBOC services most commonly for support related to mental health, relationships, and information-related requests (eg, medicolegal, service, and resource queries), expressing a higher degree of problem burden and distress relative to those who access nontext-based counseling modalities [7,33,34]. Although promising evidence for the effectiveness of TBOC interventions is starting to emerge [35-39], greater variance has been observed in the impact of these interventions for YSUs [33,40-42] than adults [43-48].

This raises questions about the factors that increase and decrease the effectiveness of these modalities, which may contribute to these dissimilar findings. We are especially interested in the perspective of e-mental health professionals who research, develop, and provide these services for whom there is little research to examine their experiences. Existing literature suggests that online counselors generally endorse the effectiveness of TBOC for YSUs, describing the tandem benefit of reduced emotional proximity to the online counselor and subsequently increased perceptions of safety that promote uninhibited discussion [49,50]. However, online counselors express concern that presenting problems featuring severity or risk may be less suitable for text-based modalities because of difficulties with comprehensive assessment; the slow pace of typed communication and not being able to offer full interventions within session time limits; misunderstandings from an absence of nonverbal cues or the presence of literacy issues, connectivity issues, and YSU distractibility; and avoidance of counseling content [49-53].

In terms of the counseling approaches used at TBOC services, emerging research indicates that many online counselors have a preference for supportive counseling frameworks with solution-focused and cognitive behavioral interventions (eg, psychoeducation, action planning, and referral) [25,33,34,41,50,52,54]. Yet, research also indicates that online counselors typically spend more time building rapport and assessing a YSU's presenting problem than setting goals, working toward them, or offering complex interventions beyond information giving or service referral [41,52,55,56]. The reasons for this preference are unclear. Some research suggests that this may be attributable to enduring challenges with comprehensive clinical assessment and the slower pace of TBOC modalities [41,52,55,56]. At least one study has revealed that engaging in more sessions was associated with greater counseling depth and alleviation in YSU psychological distress, with problem clarification and action planning processes being most correlated with reductions in distress in YSUs [41].

In view of the aforementioned literature, online counselors working via TBOC modalities appear to generally affirm its benefits for YSUs. At the same time, they identify issues related to working with more complex presentations because of limitations with communicating in a text-based milieu, which may explain the greater outcome variance YSUs experience on TBOC modalities.

Objective

This pilot study sought the perspective of e-mental health professionals in confirming the following domains and themes indicated by the literature about YSU's TBOC experiences for measurement in a larger future study: (1) motivations for selecting TBOC services (eg, safety, access, and expectations), therapeutic benefits experienced during sessions (eg, catharsis and validation), (3) experiences of TBOC ineffectiveness (eg, not making any progress), and (4) reasons for persisting with TBOC services when perceived to be ineffective.

The secondary aim of the study was to identify further constructs of interest for investigation in our future study by asking e-mental health professionals to expand on any endorsed domains. It was expected that e-mental health professionals would endorse each domain being measured, consistent with the available literature. This study is unique in its specific examination of e-mental health professional's perspectives of TBOC effectiveness and ineffectiveness factors, given their role in researching, developing, and facilitating text-based interventions. It is hoped that these findings will provide more a nuanced theory-practice perspective about the factors that may contribute to TBOC effectiveness variance for YSUs.

Methods

Design

The study used qualitative individual and focus group interviews, which were determined to be the most appropriate method of eliciting participants' perceptions about YSUs' motivations for TBOC service use and factors moderating effectiveness. Focus group interviews are described as an effective method of generating discussion about a subject area that enables participants to compare attitudes, values, and understanding in a given subject area [57]. Participants who were unable to attend focus groups were offered individual interviews as an alternative.

The semistructured interview used was developed for this study and informed by existing TBOC literature. It sought to confirm domains and themes identified in our objectives statement with participants and identify new domains and themes using 3 common steps: (1) the presentation of information about a target TBOC domain, (2) asking participants to indicate agreement or disagreement with having observed the target domain directly (during clinical consultations) or indirectly (during the course of academic research) with YSUs, and (3) inviting participants to elaborate on their experiences with the domain or its related themes and subthemes.

The interview guide used for both individual and focus group interviews can be viewed in Multimedia Appendix 1. The Consolidated criteria for REporting Qualitative research checklist was also completed for this study and can be found in Multimedia Appendix 2.

Participants

A total of 10 participants were approached and recruited for the study. Exclusion criteria in the study were having less than 5 years' experience working in e-mental health services in the capacity of clinician or researcher and having less than 5 years' experience working with YSUs. Of 10 participants, 1 was excluded from the study because of interview bias resulting from their having substantially limited knowledge and experience about TBOC services to make a meaningful contribution to the study.

The final sample of participants was 9 e-mental health professionals (5 females and 4 males), aged 27 to 67 years (mean 42.6 years, SD 14.3), currently working in direct client services (6/9) and research (2/9) and tribunal (1/9) roles; and employed in community mental health (6/9), tertiary education (2/9), and government (1/9) settings. Of the 9 participants, 6 had collegial relationships with the interviewer and were aware of the broad area of research being conducted (TBOC) but did not know specifics of the study.

Participants possessed tertiary qualifications in mental health (undergraduate degree=3/9 postgraduate degree=3/9 and doctoral degree=3/9), and they described their professional roles to be psychologists, social workers, counselors, and health scientists. Participants had 8.5 years' average experience working in e-mental health settings and 8.1 years' average experience working with YSUs in mental health settings.

Procedure

Ethical approval for the study was obtained from the University of Queensland's Behavioral & Social Sciences Ethical Review Committee. The primary author was the interviewer of this study. He was acting in the role of counseling psychologist for young people and adults at the time of the study and has postgraduate training and experience in conducting research interviews.

Participants were recruited using a word-of-mouth sampling technique, owing to the need to select e-mental health experts with diverse understanding of youth mental health and TBOC interventions. All interviews were conducted solely with the interviewer and participants. Overall, 4 participants attended individual interviews at university and hospital workplaces, and 6 participants attended 3-person mini focus group interviews at Kids Helpline. Mini focus group interviews were conducted with Kids Helpline staff because of the challenges in arranging for participants to attend traditionally sized focus, given its shift work environment. Focus groups and interviews were approximately 60 min duration in a face-to-face format (1 participant attended a telephone interview). All interviews were audio recorded and transposed to text by a professional transcription service, with the names of participants changed to ensure anonymity. All participants were followed up via email after their interviews were transcribed to ask them clarifying questions about their responses, where information was unclear in the interviewer's notes or audio transcripts.

Data Analysis

Thematic analysis was the approach taken to understanding participant's perceptions about the characteristics and motivations of YSUs accessing TBOC and factors moderating the effectiveness of these modalities. The thematic analysis methodology described by Braun and Clarke [58] was used, involving the process of developing familiarity with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing a report of findings.

The primary author initially read all transcripts, and then 1 interview transcript was assigned to each of 5 independent analysts. Analysts manually defined a set of preliminary codes that did not necessarily conform to the language used in the interview guide. The primary author then met with each analyst independently to compare their codes and search for themes in the data. Coding discrepancies between the primary author and independent analyst were discussed until a consensus was obtained. Qualitative themes were only rated once for each participant describing them, irrespective of the number of times that theme was identified. The primary author then reviewed themes across all datasets to search for overlapping themes generated by analysts and collapsed these into the fewest themes possible and renamed them accordingly. The final stages of analysis involved the authors reviewing themes and subthemes to ensure that coded extracts were valid, logical, and reasoned.

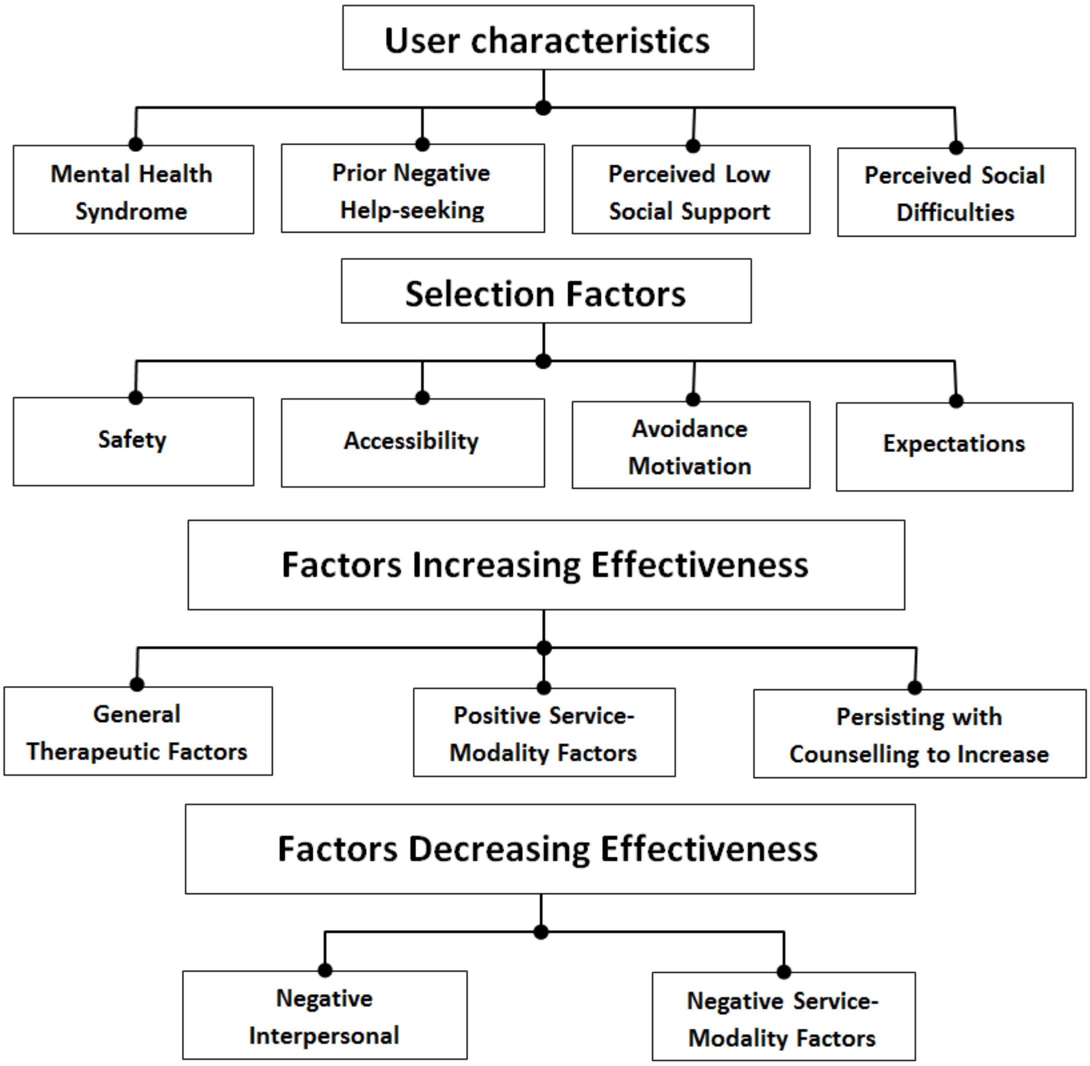
A frequency count was applied to themes to identify their commonality for our future planned studies, wherein we seek to further examine those with higher occurrence. Ratings of *very strong*, *strong*, *moderate*, and *weak* were given if >80%, >50%, >30%, and >10% of participants endorsed the theme, respectively, with cutoffs influenced by the effect size literature. Given the small sample size in this pilot study, themes endorsed by fewer than 2 participants were excluded from the analysis on the grounds of low generality.

Results

Overview

Participants confirmed 3 domains, and identified a unique domain (ie, *user characteristics*), that were related to YSUs' motivations for selecting TBOC services and their effectiveness. The following sections present qualitative data describing the experiences of participants in these 4 areas. Figure 1 shows an illustrative overview of primary domains and themes identified in the study.

Figure 1. Overview of primary domains and themes identified by text-based online counseling providers.



User Characteristics

User characteristics emerged as a unique domain for which participants described factors related to context, experience, and perception believed to precede a YSU's selection of TBOC modalities. Participants described 4 themes related to *user characteristics: prior negative help-seeking experience*, *mental health syndromes*, *limited social support*, and *perceived social difficulties*. An overview of domains and themes related to *user characteristics* is presented in Table 1.

The view that many YSUs select to use TBOC services because of a *prior negative help-seeking experience* was described by 5 of 9 participants. Participant responses were similar. The key aspect described was that YSUs often sought the safety of TBOC services following negative responses from family to their help-seeking efforts or rupture in rapport with professional workers.

Table 1. Overview of themes identified by text-based online counseling providers about perceived user characteristic domains.

Domains and themes (user characteristics)	Strength of theme	Examples of theme
Prior negative help-seeking experience	Strong	*Sometimes it occurs... there may have been a rupture within the therapeutic relationship with a face to face worker, so [YSUs] may retreat to an online service because it's perceived to be more comfortable for them that way.*
Mental health syndrome	Strong	*If you have a look at the research that Kids Helpline has done and look at the frequency of problems coming up in the online environment... what you'll find is that you get a higher frequency of mental health problems and suicidality and other indicators of more severe disturbance in the online environment suggesting that people who are really quite distressed and maybe somewhat paranoid have a strong preference to that environment compared with the telephone environment.*
Limited social support	Moderate	*When you start to explore who else [YSUs can] talk to, they feel like there is no one else that they can talk to about a particular issue. That's the reason why they are contacting in this way.*
Perceived social difficulties	Moderate	*You'll hear [YSUs] reflect on having an introverted personality, and that they'll... they just find that they are able to express themselves better in this setting.*

The view that many YSUs present to TBOC services with *mental health syndromes* was described by 5 of 9 participants. Participant responses were similar. The key aspect described was that TBOC services were commonly used by YSUs with mental ill health because of the safety associated with communicating in text-based online environments.

The view that many YSUs experience *limited social support* was described by 3 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs seeking out TBOC services to compensate for a low-density support network, perceived inability to talk to people in their existing support network, and the desire to add more support people to their established support network.

The view that many YSUs experience *perceived social difficulties* was described by 3 of 9 participants. Participant responses were variable. Key aspects that emerged were that some YSUs perceiving themselves to have communication difficulties, introverted personalities, or undesirable physical characteristics that make them socially anxious.

Selection Factors

Participants confirmed 4 themes related to their perceptions of YSUs' motivations for selecting TBOC modalities for counseling support: *safety, accessibility, avoidance motivation,* and *expectations*. An overview of domains and themes related to *selection factors* is presented in Multimedia Appendix 3.

Safety

All participants shared perceptions that confirmed *safety* as the most important motivator underpinning a YSU's selection of TBOC modalities. A total of 3 subthemes were identified within this theme.

The view that TBOC felt safer to YSUs because of *increased privacy* from its text-based interface was described by 8 of 9 participants. Participant responses were similar. The key aspect described was that YSUs were motivated to conceal their help-seeking efforts from others in their immediate environment, mostly their parents.

The view that TBOC felt safer to YSUs because of *increased control and autonomy* over the counseling process was described by 7 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs being wanting control over making disclosures and when counseling sessions end and independence in accessing a mental health service, especially when parental gatekeeping was a barrier to care.

The view that TBOC felt safer to YSUs because of *increased anonymity* when using text-based interfaces was described by 7 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs feeling able to discuss more sensitive content when online counselors could not see them or did not personally know them and conceal information leading to their personal identification in the community, especially when disclosing risk information.

Accessibility

All participants shared perceptions that confirmed *accessibility* to be an important motivator underpinning YSUs' selection of TBOC modalities. A total of 8 subthemes were identified within this theme.

The view that the *convenience and flexibility* of TBOC services increased YSU access to care was described by 8 of 9 participants. *Convenience* and *flexibility* determined to be interrelated by analysts because of their frequent cooccurrence and similarities in their features. Participant responses were variable. Key aspects that emerged were about the convenience of accessing TBOC services from one's own device and the flexibility of accessing TBOC services from any location or at any time of day.

The view that TBOC services increased YSU access to care by allowing *faster access to counseling* was described by 8 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs being able to access support at the moment of distress or crisis rather than *circumnavigating waiting lists* (see subtheme) and the disadvantage of accessing TBOC services when in crisis or distress when delays were created by high service demand.

The view that the *affordability* of TBOC services increased YSU access to care was described by 6 of 9 participants. Participant responses were similar. The key aspect described was about the unaffordability of counseling sessions to YSUs, given their developmentally limited access to money.

The view that *sourcing one's own support* by using TBOC services increased YSUs access to care was described by 6 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs being able to use TBOC services to overcome restricted access to devices or internet access, systemic barriers to accessing mental health care, accessibility issues related to service location and appointment availability, and privacy-related issues to service use.

The view that TBOC services increased YSUs' access to care by *circumnavigating waiting lists* was described by 5 of 9 participants. Participant responses were similar. The key aspect described was about YSUs being able to access care quickly because of the absence of waiting lists and a shorter intake assessment process, relative to face-to-face services.

The view that TBOC services increase YSU access to *counseling in areas of low service density* was described by 3 of 9 participants. Participant responses were similar. The key aspect described was about YSUs being able to access counseling when living in areas with no services available or services only available at very far-to-reach distances.

The view that text-based communication was a *preferred way* (for YSUs) *to communicate* that increases their likelihood of accessing care was described by 2 of 9 participants. Participant responses were similar. The key aspect described was that availability of internet-ready devices, and the popularity of text-based communication within youth culture makes TBOC services more accessible and, therefore, appealing to YSUs.

The view that TBOC services help with *overcoming transportation issues* to care was described by 2 of 9 participants. Participant responses were similar. The key aspect described was that TBOC services increased service access because they do not require YSUs to have a license, vehicle, or access to transportation.

Avoidance Motivation

Avoidance motivation emerged as a unique theme that was perceived by all participants to underlie YSUs' perceptions of *safety* about TBOC services. A total of 6 subthemes were identified within this theme.

The view that YSUs select TBOC services to minimize the chance of *being overheard or seen attending a service* was described by 8 of 9 participants. Participant responses were similar. The key aspect described was YSUs had concerns about the social consequences of being discovered accessing counseling by one's family or peers.

The view that YSUs selected TBOC services to *minimize difficult emotions* during counseling sessions was described by 7 of 9 participants. Participant responses were similar. The key aspect described was that YSUs feel uncomfortable with becoming embarrassed, vulnerable, or overwhelmed during counseling sessions, which were perceived to be minimized when using TBOC rather than face-to-face modalities.

The view that YSUs selected TBOC services to minimize *privacy and security concerns* was described by 6 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs feeling concerned about who might be able to access their private information, whether online counselors might share their personal information with known others, and their need to withhold or alter personal identifying information to enhance the security of their data.

The view that YSUs selected TBOC services to minimize the *counselors' reaction* was described by 5 of 9 participants. Participant responses were similar. The key aspect described was about YSUs having concerns that online counselors might be unfriendly, judgmental, or needing to take undesired action based on content disclosed in sessions, motivating them to reduce interpersonal feedback cues.

The view that YSUs selected TBOC services to avoid *challenging conversations* was described by 5 of 9 participants. Participant responses were similar. The key aspect described was about YSUs feeling concerned that online counselors' questions were uncomfortable, confronting, or may result in undesired action being taken based on disclosed content, motivating them to avoid these questions or lines of conversation.

The view that YSUs selected TBOC services to avoid *social interaction* was described by 3 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs seeking to avoid social interaction owing to concerns about *perceived social difficulties* (see subtheme) and the time pressure to respond to an online counselor's questions in a face-to-face environment.

Expectations

Most participants (7/9) shared perceptions that confirmed how YSUs' *expectations* about TBOC outcome motivated their access to these services. A total of 4 subthemes were identified within this theme.

The view that YSUs had *few expectations* of TBOC services was described by 5 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs either having no expectations of TBOC services or being encouraged by loved ones to use these services rather than having personal investment in the outcome.

The view that YSUs had *high treatment expectations* of TBOC services was described by 4 of 9 participants. Participant responses were variable. Key aspects that emerged were about YSUs expecting that TBOC services could assist them with issues of higher complexity and/or in a faster than realistic manner.

The view that a *prior successful interaction* on TBOC services was related to elevated YSU expectations was described by 4 of 9 participants. Participant responses were similar. The key aspect described was that YSUs were more likely to access TBOC services in return if they had previously had a beneficial counseling session.

The view that YSUs saw TBOC services as *equivalent to other counseling modalities* was described by 3 of 9 participants. Participant responses were similar. The key aspect described was that YSUs tended to view all modalities of counseling as being similar in process and producing similar outcomes.

Factors Perceived to Increase Effectiveness

Participants confirmed 3 themes to be related to factors they perceived to increase the effectiveness of TBOC: *general therapeutic benefits*, *positive service-modality factors*, and *persisting with counseling to increase benefit*. An overview of domains and themes related to *factors perceived to increase effectiveness* is presented in Multimedia Appendix 4.

General Therapeutic Benefits

This theme was confirmed by all participants who perceived that the interpersonal skills and experiences universal to counseling were related to TBOC effectiveness. A total of 3 subthemes were identified within this theme.

Feeling listened to and understood was described to be effective by 3 of 9 participants. Feeling *listened to* and *understood* were distinct subthemes that were combined by analysts because of their frequent cooccurrence and similarities in features. Participant responses were similar. The key aspect described was that YSUs feeling listened to and understood by online counselors was related to TBOC effectiveness.

Catharsis or debriefing was described to be effective by 2 of 9 participants. Participant responses were similar. The key aspect described was that YSUs sharing or processing their experiences with online counselors as a form of minimal intervention was related to TBOC effectiveness.

Feeling normalized and validated was described by 2 of 9 participants. Participant responses were similar. Feeling *normalized* and *validated* were distinct themes that were combined by analysts because of their frequent cooccurrence and similarities in features. The key aspect described was that YSUs feeling like their presenting problems were normal and accepted by the online counselor was related to TBOC effectiveness.

Positive Service-Modality Factors

This theme was confirmed by all participants who discussed service and modality factors perceived to be associated with increased TBOC effectiveness. A total of 7 subthemes were identified within this theme.

Working with less complex presenting problems was described by 6 of 9 participants to be related to increased TBOC effectiveness. Participant responses were similar. The key aspect described was that TBOC services were more effective when focused on issues with less complexity and pervasiveness that could benefit from short-term work.

Using TBOC services as a *stepping stone to more intensive counseling support* was described by 5 of 9 participants to be related to increased TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that TBOC services were used by YSUs to trial and build comfort with the counseling process and as a pathway to face-to-face counseling, especially for those with complex presenting problems.

Of 9 participants, 4 described that text-based communication allowed YSUs a greater *ease of expression or thought organization*, which was related to increased TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that text-based communication allowed YSUs to better articulate their internal experiences and leverage the latency of text-based communication to process their responses to counseling questions.

Another 4 of 9 participants discussed that YSUs valued TBOC modalities for their *crisis use*. Participant responses were similar. The key aspect described was that YSUs benefit from accessing TBOC services during a crisis because of the *faster access to counseling* (see subtheme) possible.

The *written record of information* produced by many TBOC modalities was described to be related to its effectiveness by 3 of 9 participants. Participant responses were similar. The key aspect described was that YSUs could benefit from accessing their counseling transcript to remember information and strategies provided during sessions.

Teaching YSUs *problem self-management strategies* was described to increase TBOC effectiveness by 2 of 9 participants. Participant responses were similar. The key aspect described was that interventions that facilitate self-control and self-management were associated with increased TBOC effectiveness.

Therapist assistance was described to increase TBOC effectiveness by 2 of 9 participants. Participant responses were similar. The key aspect described was that interventions were generally more effective when delivered by an online counselor as opposed to being delivered via self-help programs.

Persisting With Counseling to Increase Benefit

This theme was confirmed by 4 of 9 participants who described the perception that some YSUs did not appear to make progress toward their presenting problem when using TBOC services but continued to access irrespectively. Participant responses were variable. Key aspects that emerged were about YSUs accessing TBOC services without consideration of its effectiveness, being unable to articulate how TBOC services help them, and being motivated by the interpersonal benefits of the interaction rather than progress toward their presenting problem.

Factors Perceived to Decrease Effectiveness

Participants confirmed 2 themes related to their perceptions about what decreased TBOC effectiveness: *interpersonal factors reducing effectiveness* and *negative service-modality factors*. An overview of domains and themes related to *factors perceived to decrease effectiveness* is presented in Multimedia Appendix 5.

Interpersonal Factors Reducing Effectiveness

This theme was confirmed among all participants who discussed interpersonal factors perceived to affect the TBOC process and reduce its effectiveness. A total of 11 subthemes were identified within this theme.

Of 9 participants, 7 described that a YSU's *problem not improving or* (online counselors using) *ineffective techniques* reduced TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about online counselors experiencing focusing and goal setting difficulties during sessions, a poor fit between the YSUs presenting problem and what TBOC modalities can provide, and a YSU's expectations of TBOC not being met.

Rupture in rapport was described by 7 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about YSUs having negative interpersonal experiences with online counselors (eg, judgment or trivializing their problem), discomfort in counseling sessions that affected the therapeutic relationship, or feeling betrayed by the service when an external response was required in response to high-risk situations (eg, suicide attempt).

A YSU's *focus on rapport instead of* (working toward) *goals* was described by 6 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about a minority of long-term YSUs developing a dependent relationship with TBOC services over time and how YSUs' motivation to achieve their goals could shift to seeking *general therapeutic benefits* (see subthemes) when progress was limited.

Poor conversion of counseling into postsession action was described by 5 of 9 participants to reduce TBOC effectiveness. Participant responses were similar. The key aspect described was that YSUs were sometimes unwilling to use counseling content or unsure about which next steps to take to make progress toward overcoming their presenting problems.

YSUs *desiring greater service control* was described by 5 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about YSUs engaging in various behaviors to overcome TBOC service access boundaries, such as falsifying personal information, accessing through different service modalities, becoming more demanding of an online counselor's availability, and disclosing crisis information to have their service requests prioritized.

Incongruent client-counselor goals were described by 4 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about disagreements between client-counselor regarding counseling goals and methods, such as whether to focus on supportive counseling versus clinical interventions, contacting a YSU's mental health workers to create consistency in counseling work, and transitioning to other counseling modalities or services considered to be more suitable in addressing a YSU's presenting problems.

Having *unclear goals or reasons for counseling* was described by 4 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about YSUs having low purpose, readiness, or motivation for accessing TBOC services; having difficulties articulating counseling goals or understanding what counseling can offer them; and interpersonal rather than clinical motivations for accessing TBOC services.

Experiencing *misunderstandings or literacy issues* were discussed by 4 of 9 participants to reduce TBOC effectiveness. *Misunderstandings* and *literacy issues* were combined by coders because of their frequent cooccurrence and having similar features. Participant responses were similar. The key aspect described was that TBOC services may not be suitable for YSUs with literacy, learning, or intellectual issues that may impair their ability to effectively use or comprehend text-based communication.

YSUs experiencing *low readiness, motivation, and self-confidence* for change was described by 4 of 9 participants to reduce TBOC effectiveness. Participant responses were similar. The key aspect described was that YSUs having the aforementioned experiences may not be in a state to make optimal use of counseling interventions.

The online *counselor going off topic or being unsure how to help* was described by 3 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that online counselors sometimes feel unclear about how to work with YSUs because of the absence of personal or assessment information provided and feeling less competent with online interventions.

Producing *outcomes with only short-term benefit* was described by 2 of 9 participants to reduce TBOC effectiveness. Participant responses were similar. The key aspect described was that short-term outcomes were sometimes indicative of less impactful *general therapeutic benefits* (see subtheme) rather than long-term impact on a presenting problem.

Negative Service-Modality Factors

This theme was confirmed among all participants who discussed service delivery and modality factors perceived to reduce TBOC effectiveness. A total of 8 subthemes were identified within this theme.

Working with complex problems was described by 8 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were about complex problems having a poorer fit with TBOC modalities because of their *slow pace or lack of time to make a difference* and *challenges assessing presentations* (see subthemes); being less responsive to TBOC interventions in terms of directly addressing extrinsic factors, such as relationships or systemic issues; and requiring more specialized interventions and services to overcome.

A *poor timeliness of response* to service requests was described by 7 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that YSUs were less likely to use or reuse TBOC services if they had to wait too long because of the window being missed for support, change occurring with the passage of time, or their feeling upset and no longer wanting support.

Challenges assessing presentations were described by 6 of 9 participants to reduce TBOC effectiveness. Participant responses were similar. The key aspect described was that clinical assessment that took place entirely using text-based communication took longer and reduced its accuracy and comprehensiveness, especially when presenting problems were vague, complex, or involved risk-related issues.

TBOC services offering *too much anonymity or few barriers* was described by 5 of 9 participants to reduce their effectiveness. Participant responses were similar. The key aspect described was that reducing service barriers to entry sometimes resulted in YSUs accessing with unnecessary or inappropriate presentations.

The *lack of nonverbal conversational cues* present in text-based communication was described by 4 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that the absence of nonverbal conversational cues reduced identifiability of YSUs accessing with complex, crisis, or inappropriate presenting problems; feedback from YSUs about intervention effectiveness; and the effectiveness of rapport building and communication fluency.

Environmental distractions were described by 3 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that *environmental distractions* created delays in YSU responses and distractions away from counseling content and other personal activities (eg, schoolwork and vocational work).

The *slow pace or lack of time to make a difference* in TBOC sessions was described by 3 of 9 participants to reduce TBOC effectiveness. Participant responses were similar. The key aspect described was that text-based communication was slower than verbal communication, which reduced the amount of time available in a counseling session and the subsequent time to make a difference to one's presenting problems.

Technical or connectivity issues were discussed by 2 of 9 participants to reduce TBOC effectiveness. Participant responses were variable. Key aspects that emerged were that when YSUs had a poor internet connection, there was a greater likelihood of session lag and dropout that resulted in session disruption and negative user experiences.

Discussion

Principal Findings

This study aimed to examine e-mental health professionals' perspectives about what motivates YSUs to select TBOC services and the factors that influence the effectiveness of these interventions, with a view to confirm domains and themes described in the literature and identify novel phenomenon.

User characteristics was a unique domain in the study, encompassing participants' views about YSUs' contextual experiences that preceded contact with TBOC services. Participants' view that YSUs commonly experience *mental health syndromes* is in line with literature indicating greater frequency and severity of mental health presentations on TBOC compared with other e-mental health modalities [7,19,25,33,59]. The view that YSUs often have *limited social support* is also consistent with the help negation literature and how young people have a tendency to negatively appraise and turn down available support, with the exception of helplines that are perceived to be a safer form of support [60]. Participants' perspective that many YSUs have *prior negative help-seeking experiences* is in line with evidence that negative past help-seeking experiences are a substantial barrier to future help-seeking for young people [60], suggesting that they may turn to TBOC services following these responses to their help-seeking efforts. Finally, participants' view that YSUs commonly experience *perceived social difficulties* was a unique finding indicating that in addition to communication preferences, some may prefer to access TBOC services because of social anxiety symptoms that are reduced when leveraging the safety of text-based communication.

Participants' views confirmed *selection factors* as a domain describing the reasons YSUs seek TBOC services. *Safety* and *accessibility* were viewed as the strongest motivators for YSUs to access TBOC services consistent with existing literature about their desire for privacy, anonymity, and control [6,26,28,30,61] as well as their struggles with financial, gatekeeper, transportation, and convenience-related barriers to mental health care [23,30,62-65]. *Avoidance motivation* and its subthemes were a unique theme among participants, which provided context to YSUs' underlying motivations for seeking *safety* from TBOC services as method of coping with threatening or uncomfortable situations. Finally, *expectations* of counseling were commonly viewed to have a polarized influence on YSUs access to TBOC services, consistent with existing literature [31,40].

Participants' views confirmed *factors perceived to increase effectiveness* as a domain describing positive predictors of TBOC outcome. Herein, *general therapeutic benefits* stemming from online counselors' interpersonal skills were strongly perceived to be related to TBOC effectiveness, in line with literature indicating the commonality and effectiveness of person-centered counseling with YSUs at e-mental health services [29,41,66,67]. *Service-modality factors increasing effectiveness* were consistent with the views of other e-mental health professionals and their belief that text-based interventions are less appropriate for primary intervention of complex mental health issues and, instead, better positioned as adjunctive interventions that support self-management and existing face-to-face work [49,50,68,69]. Participants' views also confirmed well-established notions about the advantages of text-based communication for users in processing, planning, and reviewing messages before sending them [61] as well as research indicating the superiority of having multiple sessions of TBOC rather than single sessions [54]. Counterintuitively, however, participants reported that TBOC services were effective in *crisis* situations. One possibility is that the participants considered effectiveness from the perspective that some crisis presentations may benefit from fast support irrespective of modality-related issues (eg, child abuse risk).

Participants' views confirmed *factors perceived to decrease effectiveness* as a domain describing negative predictors of TBOC outcome. One theme, *interpersonal factors decreasing effectiveness*, partly described challenges in the online counselor's management of clinical activities in a TBOC environment, which has some support in the literature. For example, participants' views about the occurrence of goal setting issues are consistent with evidence that online counselors often underutilize goal exploration processes [41,52,55], whereas *misunderstandings* commonly stem from a *lack of nonverbal conversational cues* on text-based modalities [25,32,40,41,45,46]. Conversely, some participants' perspectives were unique to the literature. For example, *counselors going off topic or being unsure how to help* is a plausible consequence in light of the commonality of working with complex presentations and goal setting issues on these modalities [49-53]. Similarly, the *poor conversion of counseling into postsession action* may be related to YSU motivation or online counselors struggling to bridge sessions together. Interestingly, the view that short-term outcomes decrease TBOC effectiveness contradicts evidence of the long-term outcomes possible on these modalities [33,60-62]. One possibility is that short-term outcomes were conceptualized as being undesirable when working with more complex presenting problems.

Participants also believed that interpersonal challenges affecting YSUs may reduce TBOC effectiveness, which were unique findings of the study. For example, participants suggested that *rupture in rapport* affected a minority of YSUs with more complex presentations featuring attachment trauma when service boundaries were altered or enforced, which is credible, given the safety-related reasons they select TBOC services. Likewise, a YSUs' *low readiness, motivation, and self-confidence* to take action toward change might be expected to occur more frequently, given the help-seeking reluctance commonly observed among young people [23,29,31,66,67].

The second theme, *service-modality factors decreasing effectiveness*, described technical and environmental challenges to service efficiency. Herein, *working with more complex problems* was perceived to reduce TBOC effectiveness, consistent with the views of other e-mental health professionals in the literature [49,50]. This is curious, given evidence that these interventions can produce positive long-term outcomes for depression and anxiety presentations [42,68-70]. One possibility is that modality-related limitations become more difficult to manage with increased problem complexity. Indeed, in their study, Dowling and Rickwood [50] found that online counselors had a preference for nondirective person-centered interventions over directive interventions, such as cognitive behavioral therapy, because of time restrictions created by the slow pace of text-based communication and YSUs multitasking while using TBOC services. Correspondingly, participants reported a quadriad of themes that complicated intervention with complex presenting problems: (1) *challenges assessing presentations* that arise from TBOC services having *too much anonymity or few barriers*, (2) the *slow pace or lack of time to make a difference* when using text-based communication, (3) the *lack of nonverbal conversational cues* that can create *misunderstandings* in text-based communication, and (4) *environmental distractions* including *technical or connectivity issues* that affect a YSU's focus and attention on a session and its impact on session time. These modality-related limitations mirror those reported by other e-mental health professionals in the literature [41,49,50,52,55,56]. In addition, participants held a unique view that TBOC services have *too much anonymity or few barriers*, suggesting a paradoxical interplay between reducing help-seeking barriers and reduced counseling effectiveness. Finally, participants viewed *poor timeliness of response* to service user requests to reduce TBOC effectiveness, which appears to be a common experience and complain by YSUs who use TBOC services [26].

Research Implications for Online Counselors

Our findings have several implications for online counselors working with YSUs accessing TBOC services. Knowledge of *user characteristics* and *selection factors* may provide insight about possible clinical targets for counseling work, especially when a YSU's presenting reasons are unclear. For example, *user characteristics* may provide clues to help with early assessment and intervention targets. Furthermore, online counselors may benefit from training in interventions for common *mental healthsyndromes* and *perceived social difficulties* that also consider a YSU's *safety* and *avoidance motivation*. Similarly, knowledge of the *factors perceived to increasing and decreasing effectiveness* may provide insight about the fit between presenting problems and the modality-related limitations of TBOC services. For example, online counselors may experience better *fit* when presenting problems are lower in complexity and require less assessment, expectations and goals are actively negotiated, and users are encouraged to access over time to allow time to balance general counseling and the provision of self-management strategies. In contrast, online counselors may struggle against the quadriad of modality-limitations reported on TBOC services when more complex presenting problems are encountered. In these cases, using precounseling assessment questionnaires may allow online counselors to compensate for some modality-limitations to allow for a better use of session time and graduation to live counseling modalities or more specialized services. Finally, exploring methodologies to reduce *poor timeliness of response* to YSU requests (eg, feedback about delays, presession activities while waiting, and support alternatives), while providing them with feedback about the strengths and limitations of TBOC modalities, may help both parties to work together in harmony to improve outcome.

Research Limitations

There are 3 main limitations in this study that need to be considered in relation to its findings. First, the use of mini focus groups may have produced fewer themes and less diversity in participant views than if using traditionally sized focus groups. Second, the semistructured nature of the interview may have resulted in missed opportunities to develop greater depth and stronger thematic narratives, compared with using a less structured interview format. Future research should consider using broader questions to overcome this limitation. Finally, although this study was designed to be a pilot preceding a large-scale study, incorporating participants into the data refinement stage of analysis using a Delphi method would likely reduce interrater bias and increased the validity of findings and their interpretations [73].

Conclusions

This study examined e-mental health professionals' perspectives about the factors that motivate YSUs to select TBOC services and influence the effectiveness of these services. Participants believed that YSUs commonly select TBOC services to increase their sense of safety in response to concerns about their privacy, themselves, and the help-seeking process. Participants also believed that using TBOC services allowed YSUs to increase their social support and access to mental health services, with nil-to-high expectations of the outcome. Factors perceived to increase the effectiveness of TBOC services were the online counselor's interpersonal skills, leveraging the information processing benefits of text-based communication, and working with less complex presenting problems or referring YSUs with more complex issues to services better capable of supporting their needs. Factors perceived to decrease the effectiveness of TBOC services were interpersonal issues related to goal setting, postcounseling direction, and ruptured rapport. Service-modality factors decreasing effectiveness were ineffective technique, working with more complex presenting problems, poor timeliness in responding to YSU requests, and various limitations related to counseling in a text-based environment. Online counselors would profit from being aware of these factors to provide YSUs with better education, assessment, and interventions on TBOC modalities.

Conflicts of Interest

PN is a PhD candidate at the University of Queensland, which is responsible for this study, as well as an employee of yourtown, where this research took place (ie, Kids Helpline). The remaining authors declare they have no conflicts of interest.

Multimedia Appendix 1

Pilot study semi-structured interview questions.

[DOCX File , 27 KB - mental_v7i1e15564_app1.docx]

Multimedia Appendix 2

Consolidated criteria for Reporting Qualitative research (COREQ) checklist.

[PDF File (Adobe PDF File), 2562 KB - mental_v7i1e15564_app2.pdf]

Multimedia Appendix 3

Overview of themes identified by text-based online counseling providers regarding young service users' selection factors.

[DOCX File , 48 KB - mental_v7i1e15564_app3.docx]

Multimedia Appendix 4

Overview of themes related to the factors perceived to increase effectiveness that were confirmed and identified in the study.

[DOCX File , 42 KB - mental_v7i1e15564_app4.docx]

Multimedia Appendix 5

Overview of themes related to the factors perceived to decrease effectiveness domain that were confirmed and identified in the study.

[DOCX File , 45 KB - mental_v7i1e15564_app5.docx]

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Abbreviations

e-mental: electronic mental
TBOC: text-based online counseling
YSU: young service user

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Original Paper

The Role of Perceived Loneliness in Youth Addictive Behaviors: Cross-National Survey Study

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Abstract

Background: In the ever-growing and technologically advancing world, an increasing amount of social interaction takes place through the Web. With this change, loneliness is becoming an unprecedented societal issue, making youth more susceptible to various physical and mental health problems. This societal change also influences the dynamics of addiction.

Objective: Employing the cognitive discrepancy loneliness model, this study aimed to provide a social psychological perspective on youth addictions.

Methods: A comprehensive survey was used to collect data from American (N=1212; mean 20.05, SD 3.19; 608/1212, 50.17% women), South Korean (N=1192; mean 20.61, SD 3.24; 601/1192, 50.42% women), and Finnish (N=1200; mean 21.29, SD 2.85; 600/1200, 50.00% women) youths aged 15 to 25 years. Perceived loneliness was assessed with the 3-item Loneliness Scale. A total of 3 addictive behaviors were measured, including excessive alcohol use, compulsive internet use, and problem gambling. A total of 2 separate models using linear regression analyses were estimated for each country to examine the association between perceived loneliness and addiction.

Results: Loneliness was significantly related to only compulsive internet use among the youth in all 3 countries (*P*<.001 in the United States, South Korea, and Finland). In the South Korean sample, the association remained significant with excessive alcohol use (*P*<.001) and problem gambling (*P*<.001), even after controlling for potentially confounding psychological variables.

Conclusions: The findings reveal existing differences between youths who spend excessive amounts of time online and those who engage in other types of addictive behaviors. Experiencing loneliness is consistently linked to compulsive internet use across countries, although different underlying factors may explain other forms of addiction. These findings provide a deeper understanding in the mechanisms of youth addiction and can help improve prevention and intervention work, especially in terms of compulsive internet use.

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KEYWORDS

youth; problem behavior; excessive alcohol consumption; internet; gambling; loneliness

Introduction

Background

Addictive behaviors are a continuous burden to public health, affecting millions of individuals globally. Adolescents and emerging adults are particularly vulnerable to the harms of addictions, as they can disrupt healthy development [1], cause long-term health defects [2], damage social relationships [3], and devastate future financial competences [4]. It is widely known that youths typically engage in behaviors that are harmful, sometimes deviant, and place them at risk for injury, disease, and even unintentional mortality [5,6]. Hence, youths can be considered more susceptible to initiating at least some type of addictive behavior during the periods of adolescence and emerging adulthood.

Addictive behaviors are difficult to prevent and address because they originate progressively, are often concealed by the individual affected, and impact the person comprehensively on biological, psychological, and social levels [7]. Commonly, addiction is associated with substance misuse, and alcohol is still the most frequently used and misused substance among the youth [8]. Studies have consistently shown that adolescents are most likely to engage in heavy episodic alcohol consumption [9,10]. An additional challenge of addiction is that, in addition to substances, a wide range of objects and activities exist to which one can become addicted [11]. The 5th edition of the Diagnostic and Statistical Manual of Mental Disorders now recognizes behavioral addictions, such as excessive gambling, under nonsubstance-related disorders [12].

Gambling has increased its popularity as a recreational activity among the youth during the past years [13]. Even though many laws and regulations prohibit underage individuals from engaging in gambling activities, new gambling technologies, especially online gambling, allow easy and constant access to the activities, often without viable age restrictions [4,14]. Past research has found that gambling activities are typically initiated at the age of 16 years, whereas gambling problems are most common among individuals between ages 18 and 24 years [15]. Moreover, a recent study discovered that 12.3% of the youth across 5 continents qualify as problem gamblers [16].

Internet use is another everyday behavior that can become excessive or compulsive and cause significant harm to an individual over time [17]. The internet has become practically an inseparable part of people’s lives, and although its benefits are preeminent, it can interfere normal functioning and routines when used excessively. Past research on excessive internet use has identified associations with negative adolescent psychosocial development [18], mood abnormalities [19], and lower school performance [20]. Adolescents are more likely to engage in compulsive internet use, become addicted to the use, and are found to be more vulnerable to its negative effects [21].

As technology keeps advancing rapidly, it simultaneously changes the structure of the social world. People must adapt to these societal progresses quickly, and oftentimes, youths are leading this adaptation process. As modern devices allow individuals to stay connected continuously, find contacts across unprecedented distances, and even create virtual companionships, they are paradoxically becoming more disconnected from each other. This manifests in lessened face-to-face interaction with physical social connections [22] and allows for new types of social exclusion such as cyber bullying [23]. This societal change might further result in increased perceived loneliness, specifically among young individuals, to whom peer relationships are salient and exploring different social identities is relevant [24,25]. Loneliness experienced in youth can have significant consequences in terms of mental health and overall well-being [26], and a potential reason for youth addictive behaviors may lie in perceived loneliness.

Loneliness is a common and distressing experience that people typically attempt to avoid [27]. Loneliness has been challenging to define, and different typologies of it have been distinguished. Past research has generally described loneliness as a subjective feeling of an individual that occurs as a natural response to certain situations [28]. It is often accompanied by feelings of anxiety, emptiness, and social isolation [28,29]. Many background variables are associated with loneliness, but the subjective evaluation of one’s realized social relationships has been shown to be one of the most important determinants of experiencing loneliness [30].

The cognitive discrepancy model by Perlman and Peplau [27] offers a blueprint for social psychological theory of loneliness, and it is broadly used in conceptualizing loneliness. The model states that individuals experience loneliness when their personal network of social relations is either quantitatively or qualitatively deficient. When an individual’s expectations of his or her interpersonal interactions do not meet with the existing ones, it results in loneliness [27].

Loneliness can have severe and long-lasting consequences. Past research has identified loneliness as a risk factor in a range of destructive health behaviors. For instance, social isolation and loneliness are associated with a greater risk of smoking and being inactive [31]. Previous research has also linked loneliness to problematic internet use [19]. To a more severe effect, loneliness and social isolation have been consistently found to result in higher likelihood of premature mortality, emphasizing social relationships’ fundamental role in people’s life [26]. Although much research on the effects of loneliness examines adult populations, similar effects also exist among young individuals: A study on college freshmen concluded that loneliness was associated with a lower immune response, poorer sleep quality, and elevations in cortisol levels [32]. Another study found indications that loneliness increases the risk of substance use among adolescents in the United States and Russia [33].

In this study, we examine the association of loneliness with a range of youth addictive behaviors in 3 diverse countries: the United States, South Korea, and Finland. These countries were chosen for their distinct cultural features [34] while being technologically analogous, advanced, and affluent. However, rich environmental and social resources do not safeguard youths from experiencing negative emotions and engaging in destructive behaviors: youths from these cultures experience declines in global life-satisfaction and well-being in the onset and progression of adolescence [35]. In addition, negative social experiences (eg, loneliness, discrimination, and self-concept) are related to lower subjective well-being among the youth in these countries [35].

Comparing the 3 countries in terms of addictive behaviors is also feasible: Recent statistics indicate that up to 95% of the youths in these countries are active internet users [36]. Alcohol consumption among the youth in the United States and Finland is comparably high, whereas, in comparison, South Korean youths consume less alcohol [37]. Similarly, the United States and Finland show average prevalence of problem gambling, whereas the rate is below average in South Korea [38].

Objectives

Guided by the social psychological cognitive discrepancy loneliness model [27] as our theoretical framework, and existing literature on loneliness and well-being [19,26,31], this study aimed to explore how influential perceived loneliness is in youth addictive behaviors. More specifically, we investigated if loneliness is related to a range of addictions—excessive alcohol use, compulsive internet use, and problem gambling in varying ways—and if the examined relationships are consistent across different cultures.

Methods

Data Collection Procedure

Data were collected using an online survey from March to April 2017 in Finland, in January 2018 in the United States, and in February 2018 in South Korea. The study was originally conducted in Finland and expanded to the United States and South Korea for cross-national comparison. All datasets were collected with LimeSurvey software (LimeSurvey GmbH) using identical survey formats. The surveys were optimized for both computers and mobile devices. The original survey was in Finnish. It was translated into English by bilingual professional-level translators and back-translated again to ensure consistency and accurate matching of all items. The English survey was translated to Korean, which was also back-translated to English by bilingual, professional-level translators fluent in both English and Korean. The survey included measures for all target variables, including excessive alcohol use, problem gambling, compulsive internet use, and perceived loneliness. Existing translations of the validated target measures were used when available. To fit the cultural settings as accurately as possible in all 3 countries, the formatting and terminology used were slightly modified for some items [39]. The average survey response time was similar across the 3 countries, with each version of the survey taking about 15 min to complete.

Participants

The samples consisted of a total of 1212 American (mean 20.05, SD 3.19; 608/1212, 50.17% women), 1192 South Korean (mean 20.61, SD 3.24; 601/1192, 50.42% women), and 1200 Finnish (mean 21.29, SD 2.85; 600/1200, 50.00% women) participants aged 15 to 25 years. All samples were demographically balanced in terms of age, gender, and living area. The participants were recruited from a pool of volunteers administered by using Dynata: a global data collection provider that manages online panels in several countries. By managing quotas via balanced start methodology, it is possible to attain data that are consistent and match the demographic profile of each examined country. Owing to the convenience sampling with set quotas, nonresponse rates cannot be reported. There are no missing data. The local Academic Ethics Committee approved this research before implementation. Participation in the study was anonymous and voluntary. All ethical guidelines were followed.

Measures

The participants were asked to provide some key demographic information, including age, gender, and living situation. This information was acquired through individual questions in the surveys. Living situation was asked with the inquiry: Are you currently... with answer choices ranging from “Living alone?” to “Living with parents” or “Other.” For the analysis, living situation was recoded into a “Living alone” dummy variable (0=no, 1=yes). This variable was included in the analyses to account for the participants’ social disposition through living situation.

To analyze the relationship between loneliness and a range of addictive behaviors, we employed validated and reliable measures for all target addictive behaviors. To identify excessive alcohol use among the youth, the 3-item Alcohol Use Disorders Identification Test-Consumption (AUDIT-C) was used. The AUDIT-C is a brief, reliable, and effective way of measuring hazardous drinking habits in a survey [40]. The questionnaire is validated for several populations and has been found to perform well in the screening of alcohol misuse across studies [41]. The South Oaks Gambling Screen (SOGS) was utilized to measure the frequency and intensity of gambling behavior. The SOGS is a reliable (alpha=.90 in the US sample, alpha=.82 in the Korean sample, and alpha=.89 in the Finnish sample) and regularly used measure to screen for pathological gambling behavior [42]. Some of the test items were slightly modified to accommodate for cultural variations in gambling practices.

The Compulsive Internet Use Scale (CIUS) was used to measure compulsive internet use. The scale measures internet use behavior effectively and evaluates whether usage is compulsive [43]. The scale has good psychometric properties and reliability statistics (alpha=.95 in the United States, alpha=.95 in South Korea, and alpha=.93 in Finland). The CIUS consists of 14 items, each of which targets the consequences and states of mind involved in internet use. Responses range on a 5-point scale from 0 (never) to 4 (very often), with a higher score indicating compulsive internet use. The 3-item Loneliness Scale was used to measure perceived loneliness. The scale is a short measure originally adapted from the standard Loneliness Scale, the Revised UCLA Loneliness Scale [44]. It was designed for efficiently measuring loneliness in large-scale social surveys. We applied the short measure to keep the survey brief for young respondents. The short measure has been shown to be internally consistent with both discriminant and concurrent validity, and its results are comparable with those of the full measure [45]. The 3-item scale asks, “How often do you feel” (1) “that you lack companionship?” (2) “left out?” (3) “isolated from others?” Answer choices provided are: “1=hardly ever; 2=some of the time; and 3=often.” The variable was turned into a sum composite.

Possible confounding variables were taken into consideration. We identified 3 variables that were additionally included in the analyses because they may be confounded with loneliness; psychological distress, belonging to a friendship group, and belonging to an online community [46,47]. In addition, belonging to a friendship group and perceived loneliness were inversely correlated, making belonging to a friendship group a feasible control variable. Psychological distress was measured with the General Health Questionnaire-12. The scale has good internal consistency and reliability (alpha=.88 in all 3 country samples). Belonginess to a friendship group and an online community were evaluated with the item asking: How strongly do you feel you belong to the following? Designated groups and communities were indicated as “A friendship group? and “An online community?” Answers were provided with a 10-point Likert scale (1=not at all, 10=very strongly).

Statistical Analysis

Analyses were conducted by first calculating descriptive statistics for all variables. These are reported as means and standard deviations for continuous variables and as frequencies (n) and relational proportions (%) for categorical variables. We conducted Kruskal-Wallis tests to compare whether statistically significant mean differences exist between the 3 countries in terms of perceived loneliness, excessive alcohol use, compulsive internet use, and problem gambling.

A total of 2 separate multiple linear regression models were estimated for each country. The assumptions of ordinary least squares (OLS) regression were met, but because of heteroscedasticity of the residuals, we carried out the analyses by producing robust SEs [48,49]. The first model included 3 regression estimates for each addictive behavior in each country, with predictors and demographic factors. The second model included 3 regression estimates for each addictive behavior in each country, with predictors and demographic factors, controlling for the 3 potentially confounding psychological factors; belonging to a friendship group, belonging to an online community, and psychological distress. We also tested for potentially confounding interactions, including age and gender, but these did not change the main results concerning the relationship between loneliness and addictive behaviors. They were, hence, left out.

Tests of collinearity were run after each model to assess the variance inflation rate. No collinearity was observed in the models, with mean variance inflation factors ranging from 1.22 to 1.26, indicating only moderate correlation [50,51]. Correlations between dependent variables were also investigated. These are reported in Multimedia Appendix 1. To confirm the consistency of findings, the analyses were repeated (1) after removing potential outliers from the dataset, (2) with zero-inflated Poisson regression, and (3) with logistic regression analysis by using recommended cutoff scores for each addiction measure: ≥3 for the AUDIT-C [40,52], ≥21 for the CIUS [53,54], and ≥8 for the SOGS [55,56]. Zero-inflated Poisson regression has been noted as the most reliable regression model and especially suitable for addiction research having excess zeros in the data. This also solves problems related to cutoff scores that have been discussed in addiction research [57].

Results

Descriptive Statistics

The descriptive statistics (presented in detail in Tables 1 and 2) show that perceived loneliness was proportionately high in the United States and Finland (mean 5.52 in both countries), followed by South Korea (mean 5.23). These mean differences were statistically significant when comparing the United States and Finland with South Korea (*P*<.001). Excessive alcohol use was highest in Finland (mean 4.14), followed by South Korea (mean 3.85) and the United States (mean 2.29). These mean differences were significant between the United States and South Korea (*P*<.001), the United States and Finland (*P*<.001), and between Finland and South Korea (*P*<.001). Compulsive internet use was highest among youths in South Korea (mean 23.13), followed by American (mean 21.72) and Finnish youths (mean 18.80). These mean differences were significant between the United States and South Korea (*P*<.001) and between South Korea and Finland (*P*<.001). Mean problem gambling scores were highest in Finland (mean 1.60), followed by the United States (mean 1.34) and South Korea (mean 1.04). These mean differences were significant between all 3 countries (*P*<.001 in each country comparison).

Table 1. Descriptive statistics.

Variable	United States		South Korea		Finland	
	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
Excessive alcohol use	2.29 (2.69)	0-13	3.85 (3.51)	0-13	4.14 (2.98)	0-13
Compulsive internet use	21.72 (13.54)	0-56	23.13 (12.81)	0-–56	18.80 (11.13)	0-56
Problem gambling	1.34 (2.69)	0-20	1.04 (2.86)	0-20	1.60 (2.56)	0-20
Perceived loneliness	5.52 (1.86)	3-9	5.23 (1.73)	3-9	5.52 (1.78)	3-9
Belonging to friends	6.72 (2.62)	1-10	6.80 (2.21)	1-10	6.83 (2.48)	1-10
Belonging online[a]	5.38 (2.69)	1-10	4.38 (2.48)	1-10	5.03 (2.60)	1-10
Psychological distress	13.49 (6.75)	0-36	13.61 (5.98)	0-36	14.15 (6.34)	0-36
Age	20.05 (3.19)	15-25	20.61 (3.24)	15-25	21.29 (2.85)	15-25

[a] Belonging to an online community.

Table 2. Descriptive statistics of categorical variables.

Variables	United States, n (%)	South Korea, n (%)	Finland, n (%)
Gender			
Male	604 (49.83)	591 (49.58)	600 (50.0)
Female	608 (50.17)	601 (50.42)	600 (50.0)
Living alone (yes)	136 (11.2)	139 (11.7)	396 (33.0)

Results of Model 1

According to our model 1, loneliness was significantly associated with alcohol use in the United States (beta=.12; *P*<.001) and South Korea (beta=.06; *P*=.02), but not in Finland (beta=.01; *P*=.82). Out of the demographic factors, higher age was significantly related to excessive alcohol use across the 3 countries. The male gender predicted excessive alcohol use in the United States (beta=–.10; *P*<.001) and Finland (beta=–.06; *P*=.03) but not in South Korea (beta=–.04; *P*=.13). Living alone was a statistically significant predictor of excessive alcohol use in South Korea (beta=.10; *P*=.001; see Table 3). Compulsive internet use was significantly associated with loneliness in all countries (beta=.41, *P*<.001 in the United States; beta=.30, *P*<.001 in South Korea; and beta=.28, *P*<.001 in Finland). Lower age was a significant predictor of compulsive internet use in South Korea (beta=–.16; *P*<.001) and Finland (beta=–.13; *P*<.001). In the United States, the male gender (beta=–.05; *P*=.04) and living alone (beta=.06; *P*=.03) predicted compulsive internet use (Table 4).

Table 3. Main effects of ordinary least squares regression models with robust standard errors predicting excessive alcohol use (Alcohol Use Disorders Identification Test-Consumption) in 3 countries.

Model	United States				South Korea				Finland			
	B[a]	SE	Beta	*P* value	B	SE	Beta	*P* value	B	SE	Beta	*P* value
Model 1												
Constant	–4.9[b]	0.50[b]	—[c]	<.001[b]	–5.1[b]	0.69[b]	—	<.001[b]	–.51	0.67	—	.44
Perceived loneliness	.18[b]	0.04[b]	.12[b]	<.001[b]	.13[b]	0.06[b]	.06[b]	.02[b]	0.01	0.05	0.01	.82
Age (years)	.35[b]	0.02[b]	.41[b]	<.001[b]	.42[b]	0.03[b]	.38[b]	<.001[b]	.24[b]	0.03[b]	.23[b]	<.001[b]
Gender[d]	–.53[b]	0.14[b]	–.10[b]	<.001[b]	–.28	0.18	–.04	.13	–.37[b]	0.17[b]	–.06[b]	.034[b]
Living alone[e]	0.27	0.24	0.03	.27	1.1[b]	0.31[b]	.10[b]	.001[b]	0.28	0.19	0.04	.15
R^2	0.21	—	—	—	0.18	—	—	—	0.06	—	—	—
Model 2												
Constant	–5.5	0.58	—	>.001	–7.1[b]	0.90[b]	—	<.001[b]	–1.9	0.83	—	.02
Perceived loneliness	0.07	0.04	0.05	.13	.22[b]	0.06[b]	.11[b]	.001[b]	–.02	0.06	–.01	.68
Age (years)	.33[b]	0.02[b]	.40[b]	<.001[b]	.42[b]	0.03[b]	.39[b]	<.001[b]	.22[b]	0.03[b]	.21[b]	<.001[b]
Gender[d]	–.56[b]	0.14[b]	–.10[b]	<.001[b]	–.33	0.19	–.05	.07	–.70[b]	0.17[b]	–.12[b]	<.001[b]
Living alone[e]	0.26	0.24	0.03	.27	.95[b]	0.31[b]	.09[b]	.003[b]	0.3	0.18	0.05	.11
Belonging to friends	0.06	0.03	0.06	.06	.25[b]	0.05[b]	.16[b]	<.001[b]	.24[b]	0.04[b]	.20[b]	<.001[b]
Belonging to an online community	0.02	0.03	0.02	.52	–.08	0.04	–.06	.05	–.12[b]	0.03[b]	–.10[b]	.001[b]
Psychological distress	.08[b]	0.01[b]	.20[b]	<.001[b]	0.01	0.02	0.02	.59	.10[b]	0.01[b]	.21[b]	<.001[b]
R^2	0.24	—	—	—	0.2	—	—	—	0.12	—	—	—

[a] Unstandardized regression coefficient.

[b] Statistically significant results (*P*<.05).

[c] Value not applicable.

[d] Gender reference category male.

[e] Living alone measured with a dummy variable (0=No, 1=Yes).

Table 4. Main effects of ordinary least squares regression models with robust standard errors predicting compulsive internet use (Compulsive Internet Use Scale) in 3 countries.

Model	United Sates				South Korea				Finland			
	B[a]	SE	Beta	*P* value	B	SE	Beta	*P* value	B	SE	Beta	*P* value
Model 1												
Constant	8.2[b]	2.6[b]	—[c]	.002[b]	23.6[b]	2.5[b]	—	<.001[b]	19.8[b]	2.6[b]	—	<.001[b]
Perceived loneliness	3.02[b]	0.21[b]	.41[b]	<.001[b]	2.2[b]	0.22[b]	.30[b]	<.001[b]	1.8[b]	0.18[b]	.28[b]	<.001[b]
Age (years)	–.06	0.11	–.01	.58	–.63[b]	0.11[b]	–.16[b]	<.001[b]	–.51[b]	0.11[b]	–.13[b]	<.001[b]
Gender[d]	–1.5[b]	0.72[b]	–.05[b]	.04[b]	0.54	0.7	0.02	.44	0.24	0.62	0.01	.7
Living alone[e]	2.7[b]	1.2[b]	.06[b]	.03[b]	0.78	1.1	0.02	.48	–.40	0.68	–.02	.56
R^2	0.18	—	—	—	0.11	—	—	—	0.09	—	—	—
Model 2												
Constant	–3.0	2.9	—	.3	6.3	3	—	.04	9.3	3.1	—	.003
Perceived loneliness	2.2[b]	0.23[b]	.30[b]	<.001[b]	1.6[b]	0.24[b]	.21[b]	<.001[b]	1.4[b]	0.21[b]	.23[b]	<.001[b]
Age (years)	–.07	0.11	–.02	.52	–.35[b]	0.11[b]	–.09[b]	.001[b]	–.34[b]	0.11[b]	–.09[b]	.002[b]
Gender[d]	–1.2	0.68	–.04	.09	0.26	0.67	0.01	.7	0.64	0.63	0.03	.31
Living alone[e]	2.5[b]	1.1[b]	.06[b]	.02[b]	0.62	1	0.02	.55	–.52	0.66	–.02	.43
Belonging to friends	0.13	0.15	0.02	.41	.51[b]	0.18[b]	.09[b]	.01[b]	–.12	0.14	–.03	.37
Belonging to an online community	1.4[b]	0.14[b]	.27[b]	<.001[b]	1.2[b]	0.16[b]	.24[b]	<.001[b]	.98[b]	0.13[b]	.23[b]	<.001[b]
Psychological distress	.54[b]	0.06[b]	.27[b]	<.001[b]	.48[b]	0.08[b]	.22[b]	<.001[b]	.29[b]	0.06[b]	.16[b]	<.001[b]
R^2	0.3	—	—	—	0.19	—	—	—	0.16	—	—	—

[a] Unstandardized regression coefficient.

[b] Statistically significant results (*P*<.05).

[c] Value not applicable.

[d] Gender reference category male.

[e] Living alone measured with a dummy variable (0=No, 1=Yes).

In addition, in model 1, problem gambling was significantly related to loneliness in all 3 countries: in the United States (beta=.10; *P*=.001), South Korea (beta=.18; *P*<.001), and Finland (beta=.11; *P*=.001). Age was significantly related to problem gambling in the United States and South Korea, but this association was inverse. In the United States, higher age associated with problem gambling (beta=.15; *P*<.001), whereas in South Korea, lower age was associated with problem gambling (beta=–.09; *P*=.01). Across the 3 countries, the male gender was highly related to problem gambling (beta=–.14; *P*<.001 in the United States; beta=–.16; *P*<.001 in South Korea; and beta=–.26; *P*<.001 in Finland). In the United States, living alone was a significant predictor of problem gambling (beta=.13; *P*=.001; Table 5).

Table 5. Main effects of ordinary least squares regression models with robust standard errors predicting problem gambling (South Oaks Gambling Screen) in 3 countries.

Model	United States				South Korea				Finland			
	B[a]	SE	Beta	*P* value	B	SE	Beta	*P* value	B	SE	Beta	*P* value
Model 1												
Constant	–.91	0.54	—[b]	.1	1.7[c]	0.40[c]	—	<.001[c]	2.4[c]	0.60[c]	—	<.001[c]
Perceived loneliness	.14[c]	0.04[c]	.10[c]	.001[c]	.21[c]	0.04[c]	.18[c]	<.001[c]	.16[c]	0.04[c]	.11[c]	.001[c]
Age (years)	.13[c]	0.03[c]	.15[c]	<.001[c]	–.05[c]	0.02[c]	–.09[c]	.01[c]	0.01	0.03	0.01	.67
Gender[d]	–.76[c]	0.15[c]	–.14[c]	<.001[c]	–.63[c]	0.11[c]	–.16[c]	<.001[c]	–1.3[c]	0.15[c]	–.26[c]	<.001[c]
Living alone[e]	1.1[c]	0.32[c]	.13[c]	.001[c]	0.42	0.25	0.07	.09	0.05	0.17	0.01	.76
R^2	0.08	—	—	—	0.06	—	—	—	0.07	—	—	—
Model 2												
Constant	–1.7[c]	0.77[c]	—	.02[c]	0.89	0.64	—	.17	3.1[c]	1.0[c]	—	.002[c]
Perceived loneliness	0.01	0.05	0	.91	.14[c]	0.04[c]	.12[c]	.001[c]	0.01	0.06	0.01	.81
Age (years)	.12[c]	0.02[c]	.14[c]	<.001[c]	–.03	0.02	–.05	.1	0	0.03	0	.94
Gender[d]	–.74[c]	0.14[c]	–.14[c]	<.001[c]	–.63[c]	0.12[c]	–.16[c]	<.001[c]	–1.4[c]	0.16[c]	–.28[c]	<.001[c]
Living alone[e]	1.0[c]	0.32[c]	.12[c]	.001[c]	0.45	0.24	0.07	.07	0.06	0.17	0.01	.75
Belong to friends	–.02	0.03	–.02	.47	–.03	0.03	–.03	.35	–.07	0.04	–.07	.11
Belonging to an online community	.16[c]	0.03[c]	.16[c]	<.001[c]	.12[c]	0.03[c]	.14[c]	<.001[c]	0.01	0.03	0.01	.83
Psychological distress	.08[c]	0.01[c]	.20[c]	<.001[c]	.03[c]	0.01[c]	.10[c]	.02[c]	.07[c]	0.02[c]	.17[c]	<.001[c]
Adjusted R^2	0.13	—	—	—	0.08	—	—	—	0.09	—	—	—

[a] Unstandardized regression coefficient.

[b] Value not applicable.

[c] Statistically significant results (*P*<.05).

[d] Gender reference category male.

[e] Living alone measured with a dummy variable (0=No, 1=Yes).

Results of Model 2

Model 2 added the potentially confounding factors to the analyses. According to the model, loneliness was significantly associated with alcohol use only within the South Korean sample (beta=.11; *P*=.001). Higher age remained a significant predictor of excessive alcohol use in all 3 countries (beta=.40; *P*<.001 in the United States; beta=.39; *P*<.001 in South Korea; and beta=.21; *P*<.001 in Finland). Similarly, the male gender continued to predict excessive alcohol use in the United States (beta=–.10, *P*<.001) and Finland (beta=–.12; *P*<.001). Living alone endured the confounds and remained a statistically significant predictor of excessive alcohol use in South Korea (beta=.09; *P*=.003).

The relationship between loneliness and compulsive internet use remained highly significant in all 3 countries: in the United States (beta=.30; *P*<.001), South Korea (beta=.21; *P*<.001), and Finland (beta=.23; *P*<.001). Lower age was also a significant predictor of compulsive internet use in South Korea (beta=–.09; *P*=.001) and Finland (beta=–.09; *P*=.002). The effects of gender were no longer observed (beta=–.04, *P*=.09 in the United States; beta=.01, *P*=.70 in South Korea; and beta=.03, *P*=.31 in Finland). Living alone persisted as a predictor of compulsive internet use among youths in the United States (beta=.06; *P*=.02).

With the added confounds, loneliness continued to significantly associate with problem gambling only within the South Korean sample (beta=.12; *P*=.001). In the United States, higher age remained associated with problem gambling (beta=.14; *P*<.001), whereas in South Korea, the effect of age was no longer significant (beta=–.05; *P*=.10). Furthermore, in model 2, the male gender was strongly related to problem gambling in all 3 countries (beta=–.14, *P*<.001 in the United States; beta=–.16, *P*<.001 in South Korea; and beta=–.28, *P*<.001 in Finland). In addition, living alone remained a significant predictor of problem gambling within youths in the United States (beta=.12; *P*=.001). Full models are reported in Tables 3 to 5.

The additional OLS regression analyses with removed potential outliers reproduced the above findings. Only excessive alcohol use became significant in model 2 of the US sample (beta=.07; *P*=.02). The supplementary robustness checks of the analyses were done by running the models with zero-inflated Poisson regression (Multimedia Appendix 1) and logistic regression analysis using cutoff scores for addictive behaviors (Multimedia Appendix 2). These analyses showed that loneliness was associated with compulsive internet use in all countries, whereas excessive alcohol use and problem gambling remained significant only in South Korea.

Discussion

Principal Findings

Analyzing data from 3 different countries, this study examined the association of perceived loneliness with different addictive behaviors among adolescents and young adults. Loneliness was consistently associated with compulsive internet use across the 3 countries: the United States, South Korea, and Finland. An association between loneliness and excessive alcohol use was observed among youths in South Korea. Similarly, loneliness was related to problem gambling among South Korean youths. These findings were consistent when testing for confounding interactions of age and gender, indicating that to an extent, loneliness is associated with addiction, irrespective of gender or age. These results provide support for previous research [19,21] and further emphasize that loneliness is a potential risk factor particularly in compulsive internet use. Youths who experience loneliness seem more likely to follow online-oriented addiction trajectories across countries. Those youths who are more fulfilled with their interpersonal relationships might experiment with other types of disruptive behaviors, such as problem gambling and excessive alcohol consumption.

Following the cognitive discrepancy loneliness model, we suggest that lonely youths might feel as though their social needs are not adequately satisfied, which manifests in spending excessive amounts of time online. It is also possible that these youths would search for meaningful, like-minded social interactions [58,59] and identities through different online communities [60].

Cultural Significance of Findings

The extent to which youths engage in different types of addictive behaviors might reveal explanatory differences about youths in their cultural settings. Within this study, we found similarities between youths in terms of loneliness and engagement in internet use. Prevalence statistics indicate that the youth in these 3 countries are skilled internet users [36], and this finding further suggests that the internet is particularly attractive to lonely youth. However, we propose that the youth living in diverse settings have different motivations for spending excessive time online: for the individualistic American and Finnish youths, the internet is a place of expressing oneself and building a presence that is loosely connected to other users, whereas collectivistic South Korean youths might seek for virtual companionship with whom to share mutual values and support with [34]. In addition, the results indicate that compulsive internet use is highly associated with younger age, emphasizing the importance of early interventions.

In South Korea, loneliness was also found to be significantly related to excessive alcohol use and problem gambling. This result might indicate that perceived loneliness among collectivistic South Korean youth results in more serious consequences than among youths in the United States and Finland [61]. Addictive behaviors may further function as a way of coping with uncertainty caused by the deviation away from the South Korean societal status quo. These results may also reflect current behavioral trends prevailing among youths across the world. Extensive Health Behaviour in School-Aged Children data found that adolescents in the United States and Finland have become more uniform in their drunkenness frequency, with overall alcohol consumption among adolescent age groups decreasing slightly [62], whereas a nationwide research on South Korean youths' health behavior recognized the increasing rate of alcohol use among the youth as a major issue [61].

In the United States and Finland, the social environment often encourages youths to participate in alcohol use and engaging in heavy forms of drinking usually takes place in social gatherings [63]. These youths might be socially satisfied, as the cognitive discrepancy loneliness theory implies. The findings of this study might additionally reveal that among American and Finnish youths, drinking alcohol is not only a characteristic behavior of the socially active but behavior that could be considered as indulgent; an allowed form of gratification, related to having fun and enjoyment [34].

Gambling, even though often practiced alone, does not seem to be a lonely endeavor for the American or Finnish youths. Loneliness was associated with higher problem gambling in all of our country samples before adding offline and online belonging, and psychological distress, into the models. After accounting for these factors, the association remained significant only in South Korea. In Finland and the United States, other psychological factors, such as belongingness to friends or psychological distress, may be stronger predictors of problem behavior. For some youths, living alone might function as a noteworthy risk factor in both, youth compulsive internet use and problem gambling, as associations between these variables were found in 2 of the samples: the United States and South Korea. It is also possible that these 2 activities are related; due to the various online gambling opportunities, gambling activities add to the overall time spent online, thus contributing to compulsive internet use. Moreover, comorbidity is a common feature of addiction and it should be acknowledged that the addictive behaviors investigated in this study might co-occur among young individuals [64,65].

South Korean culture is described as more long-term oriented than those of the United States or Finland [34]. From this cultural perspective, it is possible that lonely South Korean youths are more distressed about how their perceived loneliness might disrupt their long-term goals, which manifests in behaviors that are counterintuitive for future well-being. In addition, loneliness may be a more serious issue in a collectivistic culture: those youths who feel loneliness may experience it much direr than their counterparts in less collectivistic countries.

Limitations

Notwithstanding the strengths of the study, some limitations must be acknowledged. First, the study utilized a cross-sectional design that does not allow for concluding that the examined associations have a directional causal relationship. Second, our results show some differences across the 3 countries but cannot pinpoint what makes the differences. Future research should explore various psychological and sociocultural factors that may contribute to the differences. Finally, the problem of self-reported survey data on substance use or illicit behavior must be acknowledged as a research limitation, as these questions can be sensitive and lead to social desirability bias.

Implications

Loneliness is an encompassing and harmful experience that can impact an individual on both physical and mental levels [27,28]. Although much research has been done on the effects of loneliness on adult populations, adolescents and emerging adults are also vulnerable populations to the harms of loneliness, as well as increasingly susceptible to destructive behaviors. Therefore, examining the relationship between these 2 variables is highly important. This study analyzed multicultural data on youths aged 15 to 25 years and found significant associations between perceived loneliness and addictive behaviors, thus adding to the existing literature. These results indicate that, across diverse cultures, youths who experience loneliness also report higher engagement in destructive behavior, especially that of compulsive internet use.

On the basis of these results, it is suggested that prevention methods for compulsive internet use be improved by educating youths about the harms of excessive online usage. An existing challenge is to reach young compulsive internet users. One promising direction of prevention is the development and building of internet-based, culturally informed behavioral intervention technologies that provide real-time support and personalized feedback, as well as assist with self-monitoring about the time elapsed online [66,67]. Furthermore, a need to develop youth prevention programs to lessen experienced loneliness is recognized. Youths should also be informed about how behaviors that may seem mundane and part of the everyday life can become excessive and disrupt healthy functioning. Focusing on strengthening youths' social relationships and educating them about the harms of loneliness are additional main implications suggested by this research.

Conclusions

Analyzing data from 3 countries, this research is able to add valuable and cross-culturally comparative insight into youth addictive behaviors. By applying social psychological theory on the phenomenon, this study extends the existing understanding on youth addiction. It can offer new information for policy makers and those working with young individuals on how to better address specific youth problem behaviors. Country and culture seem to have their share in influencing and shaping the underlining reasons, or ways, as to why the youth come to engage in certain behaviors. It is emphasized that youths coming from and living in different contexts might externalize their feelings of loneliness in different ways. Although the internet is used compulsively by youths in countries across the globe, South Korean youths also might externalize feelings of loneliness by engaging in excessive drinking and problem gambling. These youths might benefit from support and counseling that guides them toward other healthier activities.

This study expands youth addiction research beyond a national boundary. It offers additional insight into how perceived loneliness relates to 3 different types of youth addictive behaviors. Implications suggest improving prevention methods in compulsive internet use by educating youths about the harms of experienced loneliness and forms of excessive behaviors.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Complementary correlation and zero-inflated Poisson regression analyses.
[DOCX File , 18 KB - mental_v7i1e14035_app1.docx]

Multimedia Appendix 2
Complementary logistic regression analysis.
[DOCX File , 14 KB - mental_v7i1e14035_app2.docx]

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Abbreviations

AUDIT-C: Alcohol Use Disorders Identification Test-Consumption
CIUS: Compulsive Internet Use Scale
OLS: ordinary least squares
SOGS: South Oaks Gambling Screen

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