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Contents

Original Papers

Original Paper

Unraveling the Black Box: Exploring Usage Patterns of a Blended Treatment for Depression in a Multicenter Study

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Abstract

Background: Blended treatments, combining digital components with face-to-face (FTF) therapy, are starting to find their way into mental health care. Knowledge on how blended treatments should be set up is, however, still limited. To further explore and optimize blended treatment protocols, it is important to obtain a full picture of what actually happens during treatments when applied in routine mental health care.

Objective: The aims of this study were to gain insight into the usage of the different components of a blended cognitive behavioral therapy (bCBT) for depression and reflect on actual engagement as compared with intended application, compare bCBT usage between primary and specialized care, and explore different usage patterns.

Methods: Data used were collected from participants of the European Comparative Effectiveness Research on Internet-Based Depression Treatment project, a European multisite randomized controlled trial comparing bCBT with regular care for depression. Patients were recruited in primary and specialized routine mental health care settings between February 2015 and December 2017. Analyses were performed on the group of participants allocated to the bCBT condition who made use of the Moodbuster platform and for whom data from all blended components were available (n=200). Included patients were from Germany, Poland, the Netherlands, and France; 64.5% (129/200) were female and the average age was 42 years (range 18-74 years).

Results: Overall, there was a large variability in the usage of the blended treatment. A clear distinction between care settings was observed, with longer treatment duration and more FTF sessions in specialized care and a more active and intensive usage of the Web-based component by the patients in primary care. Of the patients who started the bCBT, 89.5% (179/200) also continued with this treatment format. Treatment preference, educational level, and the number of comorbid disorders were associated with bCBT engagement.

Conclusions: Blended treatments can be applied to a group of patients being treated for depression in routine mental health care. Rather than striving for an optimal blend, a more personalized blended care approach seems to be the most suitable. The next step is to gain more insight into the clinical and cost-effectiveness of blended treatments and to further facilitate uptake in routine mental health care.

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KEYWORDS

cognitive behavior therapy; internet; combined modality therapy; depression; routine mental healthcare; treatment compliance; logfile analysis

Introduction

Web-based interventions for depressive disorders have been studied and applied in different ways [1]. In the general population and in primary care, mainly unguided self-help and guided Web-based interventions have been evaluated [2,3]. In controlled research settings, Web-based interventions have proven to be efficacious in the treatment of depression when compared with nonintervening [4,5], even for patients with more severe symptoms [6,7]. Direct comparisons of Web-based and face-to-face (FTF) treatment formats indicated equivalence [8], and it has been shown that guided Web-based interventions lead to better treatment outcomes compared with unguided treatments [9-11]. These effects tend to be replicated in clinical practice [12-15], although effectiveness studies of Web-based interventions for depression among routine care populations are scarce and upscaling is still limited.

For the treatment of patients in routine mental health care settings, so called *blended* formats combining digital components with FTF therapy in one integrated treatment protocol are being developed, investigated, and implemented [16]. This way of working may better suit the regular practice and skills of psychotherapists and help meet the ethical and current professional guidelines [17]. As routine care mostly involves contact with a health care professional, this already implies a form of blending. This approach also constitutes a response to reported concerns of mental health care professionals about the suitability and appropriateness of Web-based treatments without FTF contact, especially for patients with moderate to severe depressive complaints [18]. Many therapists and patients express the need for an FTF interaction in these situations [19] and the desire to use internet and mobile interventions more freely integrated into FTF therapy [20,21]. Guidance from a care provider has also been identified as a key feature to improve engagement with Web-based interventions [22-24]. Thus, among more severe and complex patient groups, it may be favorable to complement Web-based interventions with FTF treatment contacts with a professional to monitor treatment progress and symptom course (eg, suicidality) and enhance motivation, compliance, and therapeutic alliance. Furthermore, a significantly higher acceptance for blended treatment, compared with stand-alone internet interventions, was shown in a survey conducted among a wide group of European mental health stakeholders involved in receiving and providing depression treatment in the adult population [25].

Preliminary findings of the few studies conducted so far suggest that blended treatments are feasible and achieve promising results in the treatment of depression [26-31]. Predominantly positive evaluations [26,28,30], high treatment satisfaction [29], and a reduction of depressive symptoms [26-28,30] were reported. Although all these studies integrated digital components with FTF therapy, the blended formats differ regarding intensity of treatment, treatment duration, the ratio of blending and degree of flexibility, and technologies employed. The FTF and Web-based sessions in, for example, the study of Kooistra et al [29] were highly structured, whereas others provided more flexibility in order and dosage for a more adaptable approach [28,30]. All treatments were based on cognitive behavioral therapy (CBT) elements. In most studies so far, FTF sessions were combined with the use of a Web-based platform. In the blended treatment by Ly et al [27], however, a mobile phone platform, instead of a Web-based platform, was included as the digital component. The use of smartphones also facilitates the integration of ecological momentary assessment (EMA)—the real-time monitoring of contextual variables experienced in a daily life context [32]—to improve the assessment of mood and behaviors and understand their relationship [33]. Besides a diversity in the type of technology, a variety of Web-based platforms are being used. In the large-scale European study (*European Comparative Effectiveness Research on Internet-Based Depression Treatment*, ie, E-COMPARED), which was recently completed, a blended treatment protocol combining FTF sessions with Web-based, as well as mobile, elements was used [34].

Although there are many possible applications of blended treatment in mental health care, knowledge on how blended treatments should be set up optimally is still limited [35]. Blended treatments have primarily been evaluated as a treatment package, not taking into account how the individual elements, such as FTF sessions or Web-based modules, contributed to the results. The effectiveness of this form of treatment remains hard to determine because of the lack of research into the different intervention characteristics. In addition, the application of an intervention as it is designed—also referred to as treatment fidelity [36]—has important implications for the interpretation of treatment outcomes. Lack of attention to treatment fidelity increases the risk of the inability to draw solid conclusions, as treatment effects may be attributed to other factors unrelated to the treatment itself [37]. To further explore and optimize blended treatment strategies, it is thus important to obtain a full picture of what actually happens during the treatment, taking all blended components into account separately: the usage of digital elements by the patient, the Web-based feedback provided by the therapist, and the real-time contact that has taken place between patient and therapist. As the use of internet modules and mobile apps can systematically be logged, objective and detailed measures of intervention use are available. With these log data, broad and in-depth information on how patients use and proceed through the intervention can be provided along with a realistic estimation of exposure to intervention content [38]. Combining log data with self-report questionnaire data provides a rich source of information describing the usage of the different components of blended treatment protocols in routine mental health care.

In this study, set out in the context of the E-COMPARED project, we intended to unravel the different elements of a blended depression treatment for adults. The first aim of the study was to describe the usage of blended Cognitive Behavioral Therapy (bCBT), looking at all its constituent components—FTF and Web-based contact between patient and therapist and the use of Web environment and mobile app. This was conducted across 4 European countries participating in the E-COMPARED trial and using the same digital platform (*Moodbuster*) with which they provided the Web-based modules for the bCBT. The second aim was to reflect on the actual usage of the blended treatment in routine practice, as compared with the intended application of the blended treatment protocol in each country. The third aim was to compare differences in usage patterns of bCBT between primary (Germany and Poland) and specialized care settings (the Netherlands and France), and the fourth was to identify who complies with a blended treatment approach, based on usage intensity and integration of the FTF and Web-based components. This will contribute to a better understanding of which patients do (or do not) engage with the bCBT and what that engagement looks like.

Methods

Design

Data were extracted from the research database of the E-COMPARED project [39]. This study was a pragmatic, multinational, randomized controlled trial in 9 European countries (N=943) and aimed to compare the effectiveness of blended treatment for major depression with that of treatment-as-usual (TAU) [34]. The blended treatment was provided across different sites in primary or specialized mental health care services. Various Web-based platforms were used, depending on the availability of existing systems and specific needs of the participating country. Due to the technical abilities of the Moodbuster platform to log treatment use, the focus of this paper is on the 4 countries that specifically used this platform for the blended intervention, namely, Germany, the Netherlands, France, and Poland. The Moodbuster platform was also used in the United Kingdom, however, parallel to another messaging system. As the Web-based communication could not be retrieved, participants from the United Kingdom were not included in this study because of this missing component.

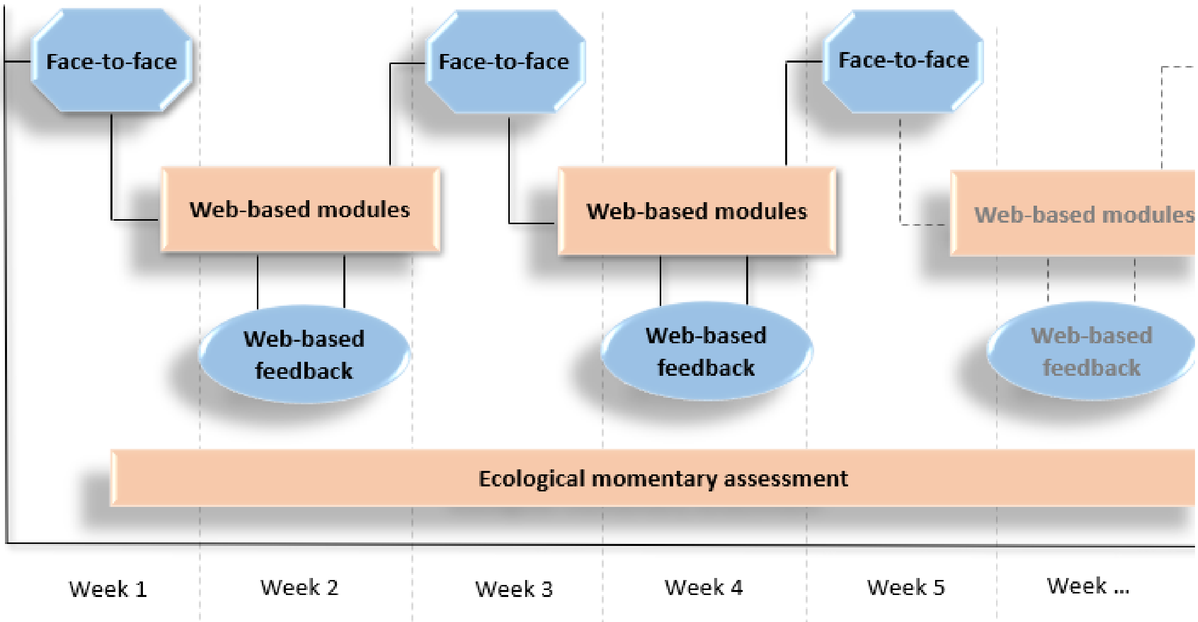
Participants

Recruitment took place in routine mental health care settings, between February 2015 and December 2017. Germany and Poland recruited patients in primary care (general practices and primary care centers) and France and the Netherlands recruited in specialized mental health care settings (outpatient clinics). Patients (aged 18 years and older) with a primary diagnosis of major depressive disorder, who were indicated for depression treatment, were asked by their health care professional if they were willing to participate in the study. If so, they were contacted by a research assistant who screened them for eligibility. Depressive disorder had to be confirmed by the Mini International Neuropsychiatric Interview (MINI) and a score of ≥5 on the Patient Health Questionnaire-9 (PHQ-9). Patients should not be receiving other psychological treatment for depression. However, there were no restrictions regarding medication use. After inclusion, patients were randomized to bCBT or TAU. TAU was the routine depression care offered in the specific treatment setting where patients were recruited and could comprise psychotherapy, pharmacotherapy, or a combination of both. Patients were followed up at 3, 6, and 12 months after baseline. Neither therapists nor patients were compensated for study participation. Further information on recruitment procedures and inclusion and exclusion criteria has been specified elsewhere [34]. The recruitment process resulted in 231 participants who were randomized to the Moodbuster blended intervention. Of these, 31 did not start the allocated intervention or had no data available on FTF contacts. Therefore, bCBT data of in total 200 participants could be included in this paper.

Blended Intervention

The blended depression treatment in this study integrates individual FTF therapy with both internet- and mobile-based interventions. FTF CBT sessions are alternated with Web-based sessions, delivered through an internet-based treatment platform called Moodbuster [40]. Moodbuster is a research platform initially developed within the ICT4Depression project [41,42] and adapted for the blended intervention within the E-COMPARED project [43]. While completing the Web-based modules in between the FTF sessions, patients receive Web-based support from their therapist in the form of a personalized written feedback message. In addition to that, patients make use of a mobile app for depression symptom monitoring and other contextual variables such as sleep, rumination, and social interactions [44]. Figure 1 illustrates the administration of the different blended components over the course of the intervention. First, we elaborate on the application of the blended treatment protocol as a whole across participating countries. Subsequently, the elements of the blended treatment are further outlined.

Figure 1. The 4 blended elements presented over time: blended cognitive behavioral therapy always starts with a 'face-to-face' session. Patients work on the Moodbuster 'Web-based modules' in between the face-to-face sessions and receive 'Web-based feedback' from their therapist through a written message on Moodbuster. During the entire treatment period, patients track their mood daily on the mobile application ('Ecological momentary assessment').



Blended Treatment Protocol

The blended treatment was provided across different European countries, with a diversity in settings and health care infrastructures. A generic bCBT protocol was set up, permitting treatment to be tailored to the local sites and situations but at the same time, preventing too much heterogeneity between blended treatments [34]. Similar bCBT was provided in all countries, including the same CBT core elements, and on the same Web-based treatment platform. The number of sessions and the ratio between FTF and Web-based sessions could vary according to local practice, but within a given range: a minimum of one-third of the sessions had to be FTF and a minimum of one-third Web-based. Also, planned treatment duration could differ across research sites. This variation was enabled to increase fit with local health care infrastructure, as the blended treatment was provided in routine care settings. The treatment duration and the ratio of FTF and Web-based sessions (see Table 1) determined the intensity of the treatment. In Germany and Poland, treatment was delivered to patients who were recruited in primary care, in a scheduled treatment duration of 7 to 13 weeks. In France and the Netherlands, patients were recruited in specialized treatment settings and the scheduled treatment duration was 16 to 20 weeks.

The blended treatment always started with an FTF meeting in which the blended format was discussed. After that, 2 mandatory Web-based modules *Introduction* and *Psychoeducation* were to be completed by patients. After completion of these 2 modules, automatic access was granted to the remaining therapeutic modules (except *Relapse Prevention*). These modules, namely, *Behavioral Activation*, *Cognitive Restructuring*, *Problem Solving*, and *Physical Exercise*, could be followed in any preferred sequence based on patient's preferences and therapist's assessment. Patients were, however, requested to complete, with guidance from the therapists, at least the modules *Cognitive Restructuring* and *Behavioral Activation* during the treatment , as these were parts of the core components of CBT. *Problem Solving* and *Physical Exercise* were seen as optional. Across countries, all treatments were intended to end with the *Relapse Prevention* module, for which therapists granted access attuned to individual patient time frames. The module flowchart is illustrated in Figure 2.

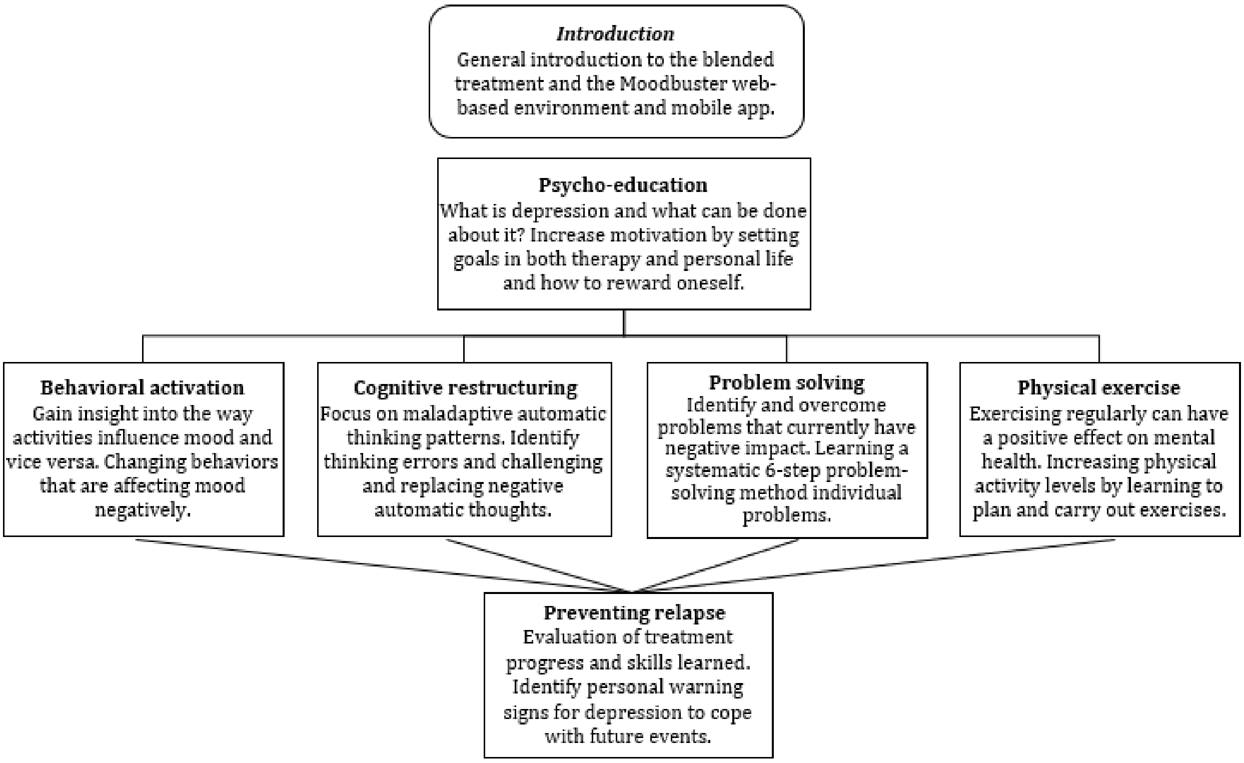
Patients were instructed to work on 1 module at a time. Moodbuster allows for differences in paths and tempo when proceeding through the intervention. The introduction pages of the modules were accessible at all times, but before entering a new module the patient had to confirm that the choice to activate that module was made in agreement with the therapist. The recommended time frame to progress through a module was 1 to 2 weeks, but more time was given if needed. Overall, flexibility was given for sequence and time spent on each module. End of treatment was defined as *last FTF* or *last Web-based contact with patient.*

Table 1. Scheduled blended treatment format per country in the E-COMPARED (European Comparative Effectiveness Research on Internet-Based Depression Treatment) trial.

Country	Type of care	Treatment duration (weeks)	Face-to-face/Web-based ratio[a]
Germany	Primary	11-13	6/10
Poland	Primary	7-10	7/6
The Netherlands	Secondary	18-20	10/9
France	Secondary	16-20	8/8

[a]Face-to-face/Web-based ratio represents the total number of recommended face-to-face and Web-based sessions.

Figure 2. Moodbuster module flowchart of the blended treatment protocol in E-COMPARED (European Comparative Effectiveness Research on Internet-Based Depression Treatment).



Blended Treatment Components

Face-to-Face Contact With Therapist

The FTF sessions were provided by therapists who were trained specifically in the blended CBT format with Moodbuster. During training, therapists were instructed on the content of the Web-based modules, how to combine FTF treatment with Web-based modules, how to structure sessions, how to use the Moodbuster platform, and how to deliver the Web-based feedback to patients. At all sites, therapists were provided with a treatment manual describing therapy sessions; regular supervision meetings were conducted; and ongoing support was available when necessary. In all countries, therapists were either licensed psychotherapists with experience in CBT or CBT therapists in training (with a university degree in psychology) who worked under the supervision of an experienced psychotherapist.

The FTF sessions followed up on the Moodbuster modules and were used to discuss content and exercises in more depth. The task of the therapist was to motivate and increase adherence to Moodbuster, as well as to guide patients through the modules and personalize the therapy. Instructions on how to structure the FTF sessions included, for example, reflecting on mood ratings, reviewing the last edited treatment module, repeating or clarifying exercises and lessons learned from the Web-based module, deepening personal therapy themes, and deciding on and discussing the next Web-based module.

Web-Based Treatment Modules for Patients

Patients were given access to the Moodbuster treatment platform with a secure personal login. Within the patient Web portal, access is given to the treatment modules, homework exercises, mood graph, calendar, and messaging system. Moodbuster is currently available in 6 languages: English, Dutch, German, Polish, French, and Portuguese.

Moodbuster comprises 1 introduction module and 6 interactive treatment modules targeting depression (see Figure 2). Each therapeutic module focusses on a specific evidence-based psychotherapeutic element, such as cognitive restructuring.

Modules comprise a series of pages that patients must complete in sequence. All modules start with a description of the goal and content of the therapeutic approach, followed by an illustrative video. Module pages contain either reading material combined with illustrations, examples, and tips as a didactical part or an interactive homework exercise where patients can apply the offered information to their own situations. All modules end with a summary followed by the administration of a questionnaire, evaluating the module and assessing severity of depressive symptoms. Screenshots of the Moodbuster website can be found in Multimedia Appendix 1.

Web-Based Feedback From Therapist

Therapists provided asynchronous Web-based feedback through the secure Moodbuster message system on a prescheduled time point in between the FTF sessions. Through the therapist Web portal, therapists were able to track their patients' progress and homework exercises on the website, as well as their mood registrations from the mobile phone app (see Multimedia Appendix 1). This information was used to provide written feedback. The goal of the Web-based feedback was to support the patient in the uptake of the content, encourage reflection, and motivate the usage of the Web-based modules. Therapists were provided with guidelines and examples for feedback messages, but specific content was adapted based on the progress of the patient.

Mobile App

Patients were prompted daily on their smartphone to rate their mood on a 1 to 10 visual analogue scale. At a random time point between 10 am and 10 pm, patients were presented with the following question: "How is your mood right now?" There was a 60-min time frame to respond to the prompt. In addition, patients could also register their mood at a self-appointed time. Besides the daily monitoring of mood, patients were also presented with questions on their sleep, activity level, social interaction, self-esteem, and rumination [44]. The monitoring of mood symptoms was presented in an interactive graph that was viewable for both patients and therapists on the website and the mobile app (see Multimedia Appendix 1). The mood graph was intended to support treatment progression and active participation of the patients. In this paper, we only included the mood registrations, as only these were used as a clinical support tool in the blended treatment.

Measurements

Patient Characteristics

Demographic variables, including gender, age, partner status, and educational level, were collected through a Web-based questionnaire at baseline. Depression severity was assessed with the PHQ-9 [45]. Patients score each of the 9 Diagnostic and Statistical Manual of Mental Disorders (4th edition) criteria on a 4-point scale, ranging from 0 (not at all) to 3 (nearly every day). The total score ranges from 0 to 27, with higher scores indicating greater symptom severity. The PHQ-9 has shown good psychometrics, with Cronbach alpha of .89 [45,46].

To assess a diagnosis of lifetime and current depression and current comorbid psychiatric disorders, the MINI [47] version 5.0 was conducted at baseline. Before being allocated to 1 of the 2 conditions, patients were asked to indicate their treatment preference (*bCBT*, *TAU*, or *no preference*) within the Web-based questionnaire.

Treatment Elements of Blended Cognitive Behavioral Therapy

Face-to-Face Contacts

To evaluate treatment fidelity, all therapists were asked to register the date, duration of the contact, and the main (module) interventions discussed after each FTF session with a patient. From this, the number and frequency of FTF sessions within the blended intervention were derived. This checklist was developed and applied within the E-COMPARED project to assess treatment exposure in both groups (TAU vs bCBT) and make it possible to compare these.

Moodbuster Website and Mobile Use (Log Files)

In the Moodbuster system, activities on the platform were systematically collected. The resulting log files contained detailed logs of system usage, including for how long the system was used, how many times the website was visited within this period, the amount of time spent on the website, patients' interaction with the Moodbuster module Web pages, and messages exchanged between the patient and the therapist. Moodbuster automatically logged when patients opened and closed module pages. This information was used to calculate frequency, duration, order, and completion of the Web-based modules, providing insight into usage patterns. As users may be interrupted within a session and leave a module page open without formally logging out, the Moodbuster system would automatically log out if a patient was inactive for >30 min. In this way, overestimation of total duration on the Moodbuster website was limited. The mobile measures were date- and timestamped, providing information on the number of mood registrations and usage weeks. Moodbuster usage data were assessed over the course of 6 months, spanning 26 weeks after the first login. Table 2 gives a full overview of the usage metrics that were extracted from the log files.

Table 2. Moodbuster usage metrics, as extracted from raw logfile data.

Usage metrics	Description
Website	
N[a] of usage weeks	Total number of weeks that Moodbuster has been used by the patient, based on the first and the last login date
N of logins	Total number of times that the patient logged on to the Moodbuster website
N of modules started	Total number of modules where the patient reached at least page 3 (confirming having started the module)
N of modules completed	Total number of modules where the patient visited all pages and filled in the end-of-module questionnaire
Average login duration	Average number of minutes spent on the Moodbuster website per login
Total usage duration	Total minutes spent on the Moodbuster website
N of messages	Total number of messages sent by the therapist or patient
Message length	Average number of characters used per message from the therapist or patient
N of contact weeks	Total number of weeks between the first and the last Web-based message from the therapist or patient
Mobile app	
N of mood registrations	Total number of times that patient registered mood state on the Moodbuster mobile app

[a]N: total number.

Analysis

For the analyses, diagnostic interview and questionnaire data were merged with the log files of the Moodbuster platform (website and mood response rates). Patient characteristics and usage of the different blended treatment components were analyzed using descriptive statistics. To assess for differences in demographics and baseline scores among the 4 countries, between mental health care settings, and between the patients being compliant and noncompliant with the bCBT format (based on engagement with FTF and Web-based components), independent samples *t* test and 1-way analysis of variance for continuous variables and chi-square tests for categorical variables were conducted. Post hoc tests (Tukey honest significant difference) were run to confirm where significant differences occurred among the countries. The statistical analyses were performed using IBM SPSS statistics version 24.0 [48]. Statistical significance was set at $P<.05$ (2-sided). Due to the exploratory nature of this study, we did not correct for multiple testing.

Ethical Approval

Ethical approval for the trials was provided at national level (Germany: Ethik Kommison DGPsychologie, Universität Trier, MB 102014; Poland: Komisja ds. Etyki Badan Naukowych, 10/2014; The Netherlands: METC VUMC, 2015.078; France: Comité de protection des personnes, Île de France V 15033-n° 2015-A00565-44) and each trial was registered in a local clinical trial register (Germany: German Clinical Trials Register DRKS00006866; Poland: ClinicalTrials.Gov NCT02389660; the Netherlands: Netherlands Trials Register NTR4962; France: ClinicalTrials.gov NCT02542891). Written informed consent was obtained from all the participants, including permission to share anonymized data across the participating E-COMPARED partners.

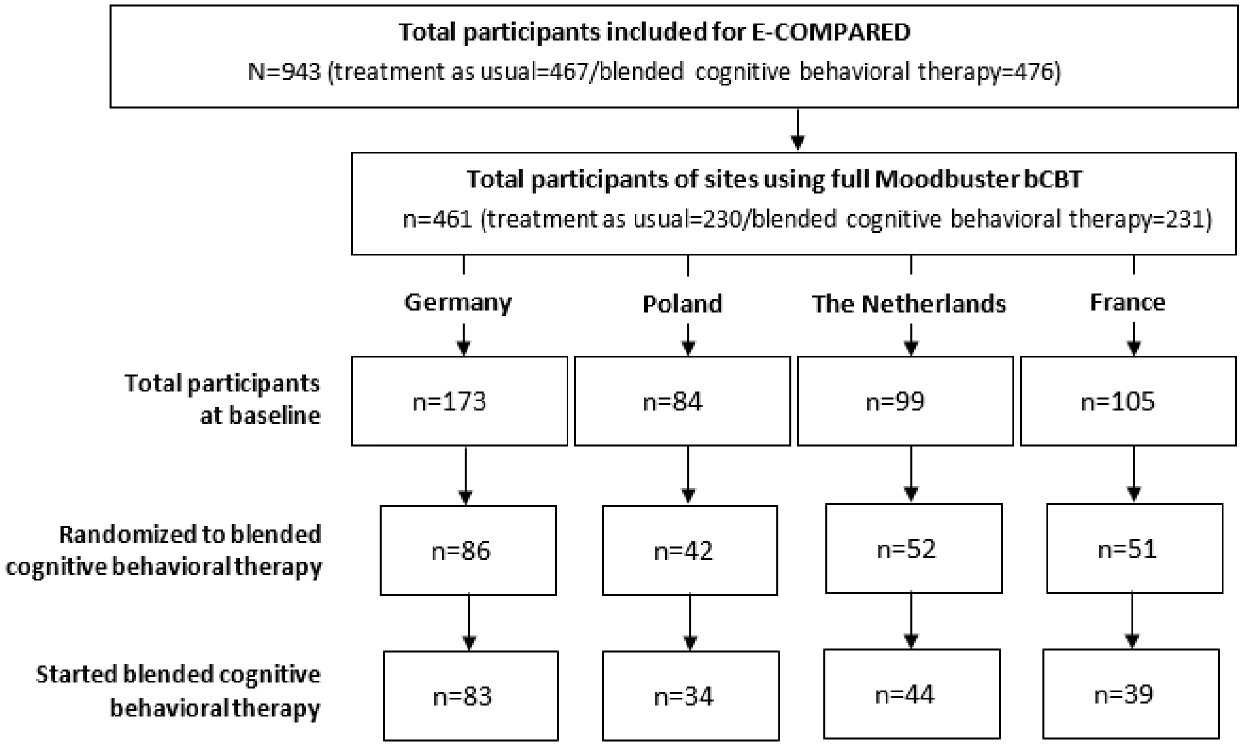
Results

Overview

Of the 231 patients randomized to the Moodbuster blended intervention, 31 (31/231, 13.4%) did not receive the allocated intervention (shown in Figure 3). Of these, 29 never attended the first scheduled treatment session or dropped out after the first FTF session and never logged in to the Moodbuster website. For the 2 patients who did use Moodbuster, there were no data available on FTF contacts. There were no significant differences in demographic or clinical characteristics between the group that did and did not start bCBT.

The patient and treatment characteristics in Tables 3 and 4 are of the 200 patients for whom data on the 4 blended components were available and who started with the allocated bCBT treatment, defined as having at least 1 FTF session and at least 1 login on the Moodbuster platform.

Figure 3. Flowchart of participants. Started blended cognitive behavioral therapy means at least 1 face-to-face session and at least 1 login on the Moodbuster platform. E-COMPARED: European Comparative Effectiveness Research on Internet-Based Depression Treatment. bCBT: blended cognitive behavioral therapy.



Patient Characteristics

Table 3 summarizes the baseline demographics and clinical characteristics of the included total sample and of each of the 4 countries separately.

The average age of the total sample was 42 years (range 18-74 years), 64.5% (129/200) were female, 51% (102/200) received higher education (postsecondary), and 58.5% (117/200) were married or were living with a partner. Overall scores on the PHQ-9 indicated moderately severe levels of depressive symptoms (PHQ>14). The number of comorbid disorders ranged from 0 to 6, including multiple anxiety disorders and substance use disorder. In total, 56.5% (113/200) had at least 1 comorbid disorder.

Baseline Differences

We looked at differences in demographics and clinical characteristics at baseline among the countries and the care settings. No significant differences among the countries or the care settings were found in patients' gender or partner status. The mean age of patients significantly differed among sites, with on average younger patients in Poland (36.4 years), compared with Germany (43.2 years) and France (45.9 years) ($F_{3,196}$=4.34; *P*=.005), but did not significantly differ between care settings ($F_{3,198}$=0.45; *P*=.51). Educational level was differently spread across the countries (X^2_6=22.6; *P*=.004), as well as between care settings (X^2_2=11.4; *P*=.003). In Germany, Poland, and France, more than half of the patients (55.5%, 61.8%, and 51.3%, respectively) received higher education, whereas in the Netherlands, only 32.8% had a postsecondary education and most patients (54.5%) had a middle education level (secondary education). No significant differences were found in baseline depression severity scores among the countries or the care settings. However, a significantly higher percentage of patients in specialized care (74.7%), compared with primary care (43.6%), had one or more comorbid disorders (X^2_1=19.1; *P*<.001), and the mean number of comorbid disorders in Germany (0.6) and Poland (0.9) was significantly lower than that in the Netherlands (1.5) and France (1.7) ($F_{3,186}$=15.35; *P*<.001). Assessed treatment modality preferences at baseline significantly differed among the countries and the care settings. In Germany and Poland (primary care), the majority of the patients expressed a preference for blended treatment (77.1% and 70.6%, respectively; primary care: 75.2%), as opposed to only 20.5% in France and 47.7% in the Netherlands (specialized care 34.9%) (X^2_6=46.1; *P*<.001). In specialized care, a significantly higher percentage expressed a preference for TAU (26.5%), as compared with primary care (6.0%) (X^2_2=34.5; *P*<.001).

Table 3. Baseline patient characteristics (N=200).

Patient characteristics	Total	Primary care		Specialized care		*P* value
		DE[a] (n=83)	PL[b] (n=34)	NL[c] (n=44)	FR[d] (n=39)	
Gender (female), n (%)	129 (64.5)	51 (61.4)	25 (73.5)	27 (61.4)	26 (66.7)	.61
Age (years), mean (SD)	41.7 (12.9)	43.2 (13.1)	36.4 (13.1)	39.4 (9.8)	45.9 (13.6)	.005
Education level, n (%)						
Low	24 (12.0)	15 (18.1)	2 (5.9)	6 (13.6)	1 (2.6)	.004
Middle	74 (37.0)	21 (25.3)	11 (32.4)	24 (54.5)	18 (46.2)	.004
High	102 (51.0)	47 (56.6)	21 (61.8)	14 (31.8)	20 (51.3)	.004
In a relationship, n (%)	117 (58.5)	51 (61.4)	24 (70.6)	24 (54.5)	18 (46.2)	.17
Baseline PHQ[e], mean (SD)	16.2 (4.7)	15.5 (4.1)	16.3 (5.0)	16.9 (5.8)	16.8 (4.6)	.33
Comorbidity, n (%)[f]	113 (60.1)	34 (41.5)	17 (50.0.9)	34 (77.3)	28 (71.8)	<.001
Treatment preference, n (%)						
Blended	117 (58.5)	64 (77.1)	24 (70.6)	21 (47.7)	8 (20.5)	<.001
TAU[g]	29 (14.5)	6 (7.2)	1 (3.3)	7 (15.9)	15 (38.5)	<.001
Non[h]	54 (27.0)	13 (15.7)	9 (26.5)	16 (36.4)	16 (41.0)	<.001

[a]DE: Germany.
[b]PL: Poland.
[c]NL: the Netherlands.
[d]FR: France.
[e]PHQ: Patient Health Questionnaire-9.
[f]≥1 comorbid disorder, as assessed with the Mini International Neuropsychiatric Interview.
[g]TAU: treatment-as-usual.
[h]Non: no treatment preference.

Usage of Blended Cognitive Behavioral Therapy

The detailed usage of the blended treatment components per country is presented in Table 4. In general, patients demonstrated a large variability in usage of the blended treatment. The observed patterns of treatment duration and ratio between FTF and Web-based sessions to some extent correspond with the intended application. Looking at the number of FTF sessions, we overall tend to see fewer differences between sites than may have been expected based on the variances in the scheduled amounts. First, we describe and reflect on intended versus observed application of the bCBT in each country (see scheduled treatment duration and session frequency in Table 1). Furthermore, we compare the application of bCBT between primary and specialized care. Next, we look at general patterns in engagement with bCBT, based on the integration of FTF and Web-based components in the treatment process. Finally, we test for differences in patient characteristics between the blended and nonblended compliant group.

Table 4. Usage of blended treatment elements per country.

Blended treatment elements	Primary care		Specialized care	
	DE[a] (n=83)	PL[b] (n=34)	NL[c] (n=44)	FR[d] (n=39)
Face-to-face sessions				
Total number of face-to-face sessions				
Mean (SD)	4.9 (0.6)	6.7 (3.5)	7.5 (5.0)	7.4 (2.3)
Range	2-5	1-18	2-32	2-9
Total duration of face-to-face contacts in minutes				
Mean (SD)	275 (42)	342 (182)	346 (230)	427 (146)
Range	105-387	60-925	90-1440	100-595
Average duration of face-to-face contact in minutes				
Mean (SD)	54.9 (8.3)	52.0 (7.3)	46.2 (5.8)	56.8 (6.7)
Range	21-77	30-70	33-64	31-67
Number of contact weeks				
Mean (SD)	9.4 (3.2)	9.5 (6.5)	16.5 (11.2)	15.8 (6.1)
Range	2-26.1	0-30.3	2-61	2-28
Moodbuster website usage				
Number of usage weeks				
Mean (SD)	12.6 (3.8)	10.6 (5.6)	13.2 (7.0)	13.9 (6.5)
Range	2.2-24.8	0.7-25.3	1.9-25.9	0-26.5
Number of logins				
Mean (SD)	16.7 (7.1)	15.8 (7.9)	11.9 (9.2)	15.5 (13.9)
Range	4-34	2-39	3-40	1-66
Number of modules started				
Mean (SD)	6.6 (1.0)	6.1 (1.3)	4.5 (1.5)	5.0 (2.0)
Range	3-7	3-7	2-7	1-7
Number of modules completed				
Mean (SD)	6.4 (1.3)	5.6 (1.7)	3.8 (1.6)	4.4 (2.1)
Range	2-7	2-7	2-7	1-7
Total usage duration in minutes				
Mean (SD)	368 (193)	396 (246)	228 (193)	332 (333)
Range	86-1199	54-1087	53-876	22-1455
Moodbuster Web-based messages usage				
Number of messages from therapist				
Mean (SD)	15.3 (5.9)	6.0 (3.2)	5.8 (3.9)	4.3 (3.7)
Range	4-39	0-13	0-14	0-12
Number of messages from patient				
Mean (SD)	8.3 (5.5)	3.8 (2.4)	4.6 (4.0)	3.1 (2.9)
Range	2-32	0-11	0-17	0-12
Average message length from therapist (number of characters)				
Mean (SD)	1282 (353)	471 (284)	741 (372)	432 (148)
Range	613-2316	140-1026	133-1636	120-702

Blended treatment elements	Primary care		Specialized care	
	DE[a] (n=83)	PL[b] (n=34)	NL[c] (n=44)	FR[d] (n=39)
Average message length from patient (number of characters)				
Mean (SD)	450 (420)	421 (373)	533 (350)	293 (125)
Range	137-3874	115-1475	132-1522	94-529
Number of contact weeks				
Mean (SD)	11.9 (3.6)	7.3 (4.7)	9.7 (7.2)	8.1 (6.0)
Range	1-23.9	0-18.1	0-24.9	0-18
Moodbuster mobile app usage				
Number of usage weeks				
Mean (SD)	14 (5.8)	12.3 (7.9)	14.7 (8.5)	14 (6.5)
Range	2.9-25.9	0-25.8	0-25.7	0-25.5
Number of mood registrations				
Mean (SD)	128.2 (92)	58 (42.8)	71.5 (72.8)	68.1 (38.5)
Range	16-442	3-204	1-352	1-158

[a]DE: Germany.
[b]PL: Poland.
[c]NL: the Netherlands.
[d]FR: France.

Germany

In Germany, 94% (78/83) of patients attended 5 FTF sessions (mean 4.9, SD 0.6), provided over a period of 9.4 (SD 3.2) weeks and paired with an average usage duration of the Moodbuster website of 12.6 weeks (SD 3.8). This is in accordance with the scheduled treatment duration of 11 to 13 weeks. It should, however, be noted that the first FTF session was not registered by therapists, as it was a technical introduction and did not include therapeutic content. Thus, in practice, the prescribed number of 6 FTF sessions was also followed. The total time spent on the website averaged 6.2 hours, with a mean usage duration of 22 min per login. All patients completed the 2 mandatory modules (Introduction and Psychoeducation) and started at least 1 optional module. The number of messages sent by therapists (mean 15.5, SD 5.9) and the length of these messages (mean 1282, SD 353) was notably higher compared with the other 3 sites. This corresponds to the scheduled ratio between FTF and Web-based session, where the Web-based part had a larger share (6 FTF/10 Web-based). All patients made use of the mobile phone app, for on average 14 weeks, registering their mood on average 128 times (range 16-442). This number of mood ratings was significantly higher than that in the other countries, as well as the expected number of ratings based on daily prompts (14 weeks×7 days=98 ratings), but can be explained by the option on the Moodbuster app permitting registration of mood at any moment without being prompted.

Poland

Patients in Poland, on average, attended 6.7 (SD 3.5, range 0-18) FTF sessions over a time period of 9.5 (SD 6.5) weeks, which is in line with the intended application (7 FTF sessions, 7-10 weeks). A patient only attended 1 FTF session (contact weeks=0) and the longest interval between the first and the last FTF session was 30.3 weeks. The Moodbuster website was used for 10.6 weeks on average (SD 5.6), with patients spending on average a total of 6 hours and 36 min on the Web. Patients received on average 6 (SD 3.2) feedback messages over a period of 7.3 (SD 4.7) weeks, which can be seen as matching the scheduled ratio of 7 FTF and 6 Web-based sessions. A total of 2 patients (2/34, 5.9%) never exchanged any Web-based message with their therapist. The mobile app was used by 91.2% (31/34) of Polish patients, with an average of 58 mood ratings (SD 42.8). On the basis of daily prompts and an average mobile usage duration of 12.3 weeks, the number of mood ratings was lower than that would have been expected (12.3×7=86 ratings).

The Netherlands

The number of FTF sessions in the Netherlands averaged 7.5 (SD 5), fewer than the prescheduled average of 10 FTF sessions and with a wide range of 2 to 32 sessions. Treatment duration was on average 16.5 weeks (SD 11.2, range 2-61) and website usage duration on average 13.2 weeks (SD 7, range 1.9-25.6). Compared with the other sites, patients in the Netherlands spent less time on the Moodbuster website, with an average of 11.9 logins and a total of 3 hours and 48 min on the Web. Therapists sent a mean of 5.8 messages to their patient (range 0-13) and on average received 3.8 messages from a patient (range 0-11). This was lower than that would be expected based on the scheduled ratio (10 FTF/9 Web-based). In 3 cases (6.8%), there was never any Web-based message exchange. A total of 6 patients (6/44, 13.6%) did not use the mobile app and 3 (3/44, 6.8%) only registered their mood once. The average number of mood registrations was 71.5 (SD 72.8), less than the expected

103 mood ratings based on the average mobile usage duration of 14.7 weeks.

France

In France, patients had on average 7.4 (SD 2.3, range 2-9) FTF sessions with their therapist over an average period of 15.8 weeks (SD 6.1, range 2-28). This is close to the scheduled number of 8 FTF sessions and treatment duration of 16 to 20 weeks. The total time spent on the Moodbuster website averaged 5 hours and 32 min, with a wide range of 22 to 1455 min. The ratio between FTF and Web-based sessions was intended to be 50/50. Patients, however, spent less time on the Web than FTF (332 vs 427 min) and received on average 4.3 (SD 3.7) Web-based messages from their therapist with only an average of 8.1 weeks between the first and the last exchanged Web-based message. A total of 7 therapist-patient pairs (7/39, 18%) did not exchange any Web-based message. The mobile app was used by 82% (32/39) of French patients. These patients used the mobile phone for an average of 14 weeks, registering their mood on average 68.1 times (SD 38.5), which is less than the expected 98 ratings based on daily prompts.

Application of Blended Cognitive Behavioral Therapy in Primary and Specialized Care

There is a clear distinction visible between primary care (Germany and Poland) and specialized care (the Netherlands and France) regarding duration and intensity in the application of the different blended components. The number of contact weeks with a therapist in primary care was significantly lower than that in specialized care (on average 9.5 weeks and 16.2 weeks, respectively; t_{198}=−6.93; P<.001). As intended, in primary care settings also, significantly fewer FTF sessions were provided than in specialized care (5.4 vs 7.5 FTF sessions; t_{198}=−4.8; P<.001). Patients in primary care, on the other hand, started and also completed significantly more Web-based modules compared with patients in specialized care settings (6.4 vs 4.8 modules started; t_{198}=8.26; P<.001 and 6.1 vs 4.1 modules completed; t_{198}=8 .71; P<.001). Also, more time, on average, was spent on the Moodbuster website in primary care (376 min) compared with specialized care (277 min) (t_{198}=2.92; P=.004). The therapists in primary care sent on average 12.6 messages, significantly more than the average of 5.1 messages sent by the therapists in specialized care (t_{198}=9.12; P<.001). Looking at the usage of the mobile app, no differences were found in number of usage weeks. Primary care patients, however, more often rated their mood with an average of 109 ratings, compared with 70 mood ratings in specialized care (t_{182}=3.31; P<.001).

General Impression of Engagement With Blended Cognitive Behavioral Therapy Components

To explore differences in patterns of engagement with the blended treatment, we looked at both the FTF and the Web-based parts of bCBT. For the FTF component, we focused on the total number of sessions (≥ or <3 FTF sessions), and for the Web-based part we summarized Moodbuster usage intensity by taking into account the number of Web-based modules started (≥ or <3 modules) and total login duration (≥ or <60 min). In total, 4 groups could be identified: *early dropouts*, *mainly Web-based*, *mainly FTF,* and *blended compliant*.

Early Dropouts

Out of 200 patients, 3 (3/200, 1.5%) received <3 FTF sessions and did not complete >2 mandatory modules (Introduction and Psychoeducation) or spent <1 hour on the Moodbuster website. These patients were considered to be early treatment dropouts.

Mainly Web-Based

A total of 8 patients (8/200, 4%) started at least 1 optional module (3 or more modules in total) by spending at least an hour on the Web on Moodbuster but had no more than 2 FTF sessions with their therapist. The average number of FTF sessions was 1.5 (SD 0.5, range 1-2), provided over a period of a maximum of 2 weeks (mean 1.0, SD 1.1) and paired with on average 5.2 (SD 2.3, range 2-9) Web-based messages from therapist. Patients started 4.6 (SD 1.3) and completed 3.8 (SD 1.4) Web-based modules on average. The mean number of logins was 9.4 (SD 3, range 4-12), spending on average a total of 3 hours and 4 min on the Moodbuster website (SD 68, range 86-272 min) and with a total average usage duration of 5.2 weeks (SD 2.3, range 2.2-9.4).

Mainly Face-to-Face

A total of 10 patients (10/200, 5%) attended 3 or more FTF sessions but did not start >3 modules (3/10) or spent <1 hour on the Web-based platform (7/10). The average number of FTF sessions in this group was 6.7 (SD 3.3, range 3-12), with a mean treatment duration of 14.5 (SD 9.7, range 3.7-28) weeks. Therapists sent on average 3.6 (SD 4, range 0-12) Web-based messages. Patients started 2.5 (SD 1.0) and completed 2.1 (SD 0.6) Web-based modules on average. The mean number of logins was 4.8 (SD 1.8, range 2-8), spending on average a total of 70 min on the Moodbuster website (SD 14, range 53-97), with a total average usage duration of 7.4 weeks (SD 6.8, range 0.7-23).

Blended Compliant

The remaining group comprised 179 patients (179/200, 89.5%) who received ≥3 FTF sessions and started ≥3 Web-based modules while spending >1 hour on the Moodbuster website. As these patients integrated both a considerable and comparable amount on FTF and Web-based activities, they were classified as compliant with the blended treatment approach. The average number of FTF sessions was 6.5 (SD 3.0, range 3-32), with a mean treatment duration of 12.8 (SD 7.1, range 2.6-61) weeks. This was paired with an average of 10.2 (SD 6.7, range 0-39) Web-based messages from the therapist. Patients started 6 (SD 1.4) and completed 5.6 (SD 1.7) Web-based modules on average. The mean number of logins was 16.3 (SD 9.4, range 3-66), spending on average a total of 6 hours and 1 min on the Moodbuster website (SD 241, range 69-1455 min), over a total average usage period of 13.4 weeks (SD 5.1, range 2-26.5). Table 5 presents the distribution of engagement groups per country.

Table 5. Engagement groups with blended cognitive behavioral therapy per country.

Engagement groups	DE[a] (n=83), n (%)	PL[b] (n=34), n (%)	NL[c] (n=44), n (%)	FR[d] (n=39), n (%)
Early dropout	0 (0)	0 (0)	2 (4)	1 (2)
Mainly Web-based	3 (3)	4 (11)	0 (0)	1 (2)
Mainly face-to-face	0 (0)	1 (2)	3 (6)	6 (15)
Blended compliant	80 (96)	29 (85)	39 (88)	31 (79)

[a]DE: Germany.
[b]PL: Poland.
[c]NL: the Netherlands.
[d]FR: France.

Blended Compliant Versus Blended Noncompliant

A small proportion of participants (31/231, 13.4%) never started with the allocated blended intervention, and of the remaining 200 patients, 21 (21/200, 10.5%) were eventually never exposed to the blended treatment format as intended (*early dropouts*, *mainly Web-based*, or *mainly FTF*). This leaves a total group of 52 patients for whom the intended blended treatment was not applied (*blended noncompliant*). Patient characteristics of the *blended compliant* and the *blended noncompliant* groups are presented in Table 6. An association between education level and treatment compliance was observed, with a significantly higher number of patients with postsecondary education in the *blended compliant* group (54.2%), compared with 36.5% in the *blended noncompliant* group (X^2_2=6.0; *P*=.048). Patients in the *blended noncompliant* group had a significantly higher average number of comorbid disorders than patients compliant with the blended treatment (t_{229}=2.107; *P*=.03). Also, a significant association between treatment preference and treatment group was observed (X^2_2=13.1; *P*=.001). Almost two-thirds (60%) of patients compliant with bCBT indicated at baseline a preference for the blended approach, as opposed to 42.3% in the *blended noncompliant* group; and one-third (33%) of the patients noncompliant with bCBT had a preference for TAU versus only 12% in the blended compliant group.

Table 6. Patient characteristics and differences between blended compliant and blended noncompliant groups.

Patient characteristics	Blended compliant (n=179)	Blended noncompliant (n=52)	Chi-square value (df)	*t* test value (df)	*P* value
Gender (female), n (%)	115 (64.2)	31 (59.6)	0.4 (1)	—[a]	.54
Age (years), mean (SD)	41.8 (12.5)	42.6 (14.2)	—	0.39 (229)	.69
Education level, n (%)					
Low	18 (10.1)	10 (19.2)	6.1 (2)	—	.048
Middle	64 (35.8)	23 (44.2)	6.1 (2)	—	
High	97 (54.2)	19 (36.5)	6.1 (2)	—	
In a relationship, n (%)	109 (60.9)	24 (46.2)	3.6 (1)	—	—
Baseline PHQ-9[b], mean (SD)	16.1 (4.9)	16.1 (6)	—	−0.06 (69)	.95
Number of comorbid disorders[c], mean (SD)	0.9 (1.1)	1.3 (1.3)	—	2.11 (229)	.03
Treatment preference, n (%)					
Blended	107 (59.8)	22 (42.3)	13.1 (2)	—	.001
TAU[d]	21 (11.7)	17 (32.7)	13.1 (2)	—	.001
Non[e]	51 (28.5)	13 (25)	13.1 (2)	—	.001

[a]Not applicable.
[b]PHQ-9: Patient Health Questionnaire-9.
[c]Assessed with the Mini International Neuropsychiatric Interview.
[d]TAU: treatment-as-usual.
[e]Non: no treatment preference.

Discussion

Principal Findings

The aim of this paper was to unravel the use of a blended CBT intervention for adult depression as applied in routine mental health care settings in 4 European countries. To the best of our knowledge, this is one of the first explorative studies opening the black box of blended treatment usage. We put a magnifying glass on bCBT and described in detail the usage of the blended components separately. Including log file data allowed us to examine objectively, and at a microscopic level, what actually happened during the Web-based part of the therapy. Furthermore, we aimed to reflect on the actual engagement with bCBT as compared with the intended application of the blended treatment protocol in each country, compare the application of bCBT between primary and specialized care settings, and explore general engagement with the bCBT components to identify who complies with a blended treatment approach.

Overall, patients demonstrated a large variability in the usage of the blended treatment. As typical patients do not exist in routine care, protocols may never be followed exactly as intended. The flexibility of the Web-based platform (Moodbuster) offered the option to tailor treatment to the individual patient, and as the results show, customization did indeed take place. Within the indicated guidelines of blending FTF and Web-based components, therapists and patients together created a more personalized blended care approach. This is in line with previous findings indicating that blended treatment is not a *fixed formula* and a tailored treatment plan combining the treatment modalities should be reached depending on patients' needs, abilities, and preferences [19,21,35,49]. That patients' treatment preferences should be taken into account in the choice of blended care is also stressed in our study by the association between baseline treatment preference and engagement with bCBT. The group of patients compliant with the bCBT format had a greater preference for the blended treatment, whereas those who did not start with the allocated bCBT indicated a preference for TAU before treatment allocation. This all can be seen as pointing in the direction of the delivery of patient-centered care and collaboration between health care provider and patient through shared decision making [50,51].

The observed patterns of treatment duration and ratio between FTF and Web-based sessions in Germany and Poland largely corresponded with the intended application. In the Netherlands and France, the Web-based part of the provided blended treatment played a less prominent role than scheduled. The mobile app was overall actively used, with patients providing on average more than two-thirds of the expected number of mood ratings. EMA counts in Germany were higher than expected, indicating that most patients rated their mood daily and on top of the prompts, also used the *self-rate* option.

In the actual application of bCBT, the distinction between primary care (Germany and Poland) and specialized care (the Netherlands and France) was visible. As by design, treatment duration in specialized care was almost twice as long as in primary care (16.2 vs 9.5 weeks) and patients attended significantly more FTF sessions (7.5 vs 5.4 FTF sessions). Nonetheless, we tend to see smaller differences in the number of FTF sessions among sites than may have been expected based on the variances in the scheduled number. Regarding the Web-based part, the patients in primary care started and completed significantly more Web-based treatment modules compared with the patients in specialized care settings; they spent on average more time on the Moodbuster website and exchanged more Web-based messages with their therapist. This reflects a more active and intensive use of the Web-based part of bCBT by patients in primary care, although the high number of exchanged Web-based messages can mainly be attributed to Germany. It should also be taken into account that in the scheduled ratio of FTF and Web-based sessions, the Web-based part of the blended treatment had a larger share in Germany. The diversity in the usage of bCBT might also be linked to the significant difference in treatment preference between primary and specialized care settings, with Dutch and French patients being less attracted to the blended approach (47.7% and 20.5%, respectively, in favor of it) compared with the Polish and German patients (77.1% and 70.6%, respectively). It should, however, be noted that TAU in primary settings was general practitioner care, which comprises mostly medication or watchful waiting.

A key observation regarding engagement was that the vast majority of patients who started with bCBT also continued with a treatment format integrating FTF and Web-based elements (bCBT *compliant* group: 179/200, 89.5%). Besides, *dropout* rates of bCBT in this study (with 31/231, ie, 13.5% never starting treatment and in total, 51/231, ie, 22.5% not compliant with the allocated treatment) were in line with those observed in traditional FTF CBT, being around 17% in randomized trials [52] and 25% in nonrandomized effectiveness studies [53]. This indicates that blended treatments can be applied to patient groups being treated for depression in routine mental health care. Patients who did not comply with the allocated bCBT seemed to have significantly more comorbidity. For patients with more complex psychological problems, it could be more difficult to individually walk through the Web-based modules and because of often occurring comorbidity, and even multimorbidity, content of the Web-based treatment modules may align less with their complaints. The use of a more transdiagnostic approach may help tailor the treatment to individual needs of patients with comorbid conditions, such as anxiety disorders. Finally, more patients in the *bCBT compliant* group were highly educated compared with the blended *noncompliant* group. Individual patient support needs may thus vary based on type and severity of mental disorder, combined with patient characteristics [54].

Limitations and Future Research

This study aimed at giving a detailed description of bCBT, considering that blended treatment in routine care is a relatively new phenomenon and insights in the actual application are lacking. Although applying a more descriptive research method has its limitations, this study contributes to the existing literature by casting light on actual bCBT engagement by patients and getting an impression of their treatment fidelity. Looking into fidelity is critical to interpretation of treatment outcomes and successful implementation [55] but is often a missing element in intervention studies. Future research should focus in more detail on factors that determine usage patterns of bCBT to optimize personalized blended treatments. In addition, blended treatment engagement could be compared with studies that have looked at self-guided or therapist-guided Web-based interventions, where often lower rates of engagement have been reported [56].

This study is only the first step in unravelling the blended treatment. Many more insights into the usage of the platform, for example, can be provided with log data, such as specific usage patterns of the Web-based treatment modules or detailed interactions with the Web-based program features. Moreover, we did not include therapist factors that might have influenced patients' usage of bCBT and how the therapists discussed the Moodbuster treatment modules and integration of components with their patients during treatment. Fine-grained process analyses, such as the influence of therapist behaviors in written feedback [57], remain an important challenge for future research. Also, of interest is further evaluation of pretreatment attitudes and acceptance of patients and therapists toward blended treatments and their potential predictors. Positive beliefs and preferences play a crucial role in the successful dissemination of new technologies [58]. Accordingly, it should be examined how to influence overall appraisal in such a way to improve uptake and implementation of bCBT in routine care. But above all, an important next step is to investigate how the actual use of the blended treatment is associated with treatment outcomes. The effectiveness of blended treatments has so far only been evaluated by looking at the treatment as a whole. The large variations in the usage of bCBT, however, underlines the importance of considering how the (combination of) different components contribute to the effects found and identifying moderating factors. In addition, engagement with the bCBT should be compared with engagement with TAU.

Conclusions

To further explore and improve blended treatment strategies, it is important to gain insight into how the different components of bCBT treatment protocols are used by patients and therapists. Protocols may, however, not be followed exactly as they are intended. The large variability in usage of the different blended elements also indicates that a search for the *best* integration may be the wrong line of reasoning. In addition, as health care systems differ largely across countries, there might be many possible ways of applying bCBT rather than 1 standard method.

The fact that the vast majority of patients who once started with bCBT also continued with a treatment integrating both FTF and Web-based elements indicates that blended treatments can be applied to a group of complex patients being treated for depression in routine mental health care. The next step is to gain more insight into the clinical effectiveness and cost-effectiveness of blended treatments and increase further uptake in routine mental health care.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Screenshots of the Moodbuster website and mobile app.

[PDF File (Adobe PDF File), 435KB - mental_v6i7e12707_app1.pdf]

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Abbreviations

bCBT: blended cognitive behavioral therapy
CBT: cognitive behavioral therapy
E-COMPARED: European Comparative Effectiveness Research on Internet-Based Depression Treatment
EMA: ecological momentary assessment
FTF: face-to-face
MINI: Mini International Neuropsychiatric Interview
PHQ: Patient Health Questionnaire
TAU: treatment-as-usual

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Original Paper

Use of Smartphone Apps, Social Media, and Web-Based Resources to Support Mental Health and Well-Being: Online Survey

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Abstract

Background: Technology can play an important role in supporting mental health. Many studies have explored the effectiveness, acceptability, or context of use of different types of mental health technologies. However, existing research has tended to investigate single types of technology at a time rather than exploring a wider ecosystem that people may use. This narrow focus can limit our understanding of how we could best design mental health technologies.

Objective: The aim of this study was to investigate which technologies (smartphone apps, discussion forums and social media, and websites and Web-based programs) people use to support their mental health and why, whether they combine and use more than one technology, what purpose each technology serves, and which features people find the most valuable.

Methods: We conducted an online survey to gather responses from members of the public who use technology to support their mental health and well-being. The survey was advertised on social media and via posters at a university. It explored usage patterns, frequently used features, and engagement with technology. To gain deeper insights into users' preferences, we also thematically analyzed open-ended comments about each technology type and suggestions for improvements provided by the respondents.

Results: In total, 81 eligible participants completed the survey. Smartphone apps were the most commonly used technology, with 78% of the participants (63/81) using them, either alone (40%) or in combination with other technologies (38%). Each type of technology was used for specific purposes: apps provided guided activities, relaxation, and enabled tracking; social media and discussion forums allowed participants to learn from the experiences of others and use that knowledge to understand their own situation; and Web-based programs and websites helped to find out how to deal on a day-to-day basis with stress and anxiety. The analysis of open-ended responses showed that although many people valued technology and felt it could support targeted activities, it was not seen as a substitute for traditional face-to-face therapy. Participants wanted technology to be more sophisticated and nuanced, supporting personalized and actionable recommendations. There was evidence that participants mistrusted technology, irrespective of the type, and had broader concerns regarding the impact of overuse of technology.

Conclusions: People use different types of technology to support their mental health. Each can serve a specific purpose. Although apps are the most widely used technology, mixing and matching different types of technology is also common. Technology should not be seen as a replacement for traditional psychotherapy, rather it offers new opportunities to support mental health as part of an overall ecosystem. People want technology to be more nuanced and personalized to help them plan informed actions. Future interventions should explore the use of multiple technologies and their combined effects on mental health support.

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KEYWORDS

mental health; mobile apps; mHealth; social media; self-instruction programs, computerized

Introduction

Background

Given the prevalence of mental health issues, such as depression, anxiety, and stress, there is an urgent need to help people manage their mental health. Stress, for example, accounts for 37% of all work-related ill health cases and 45% of all working days lost because of ill health in the United Kingdom [1], whereas depression alone affects 98.7 million people worldwide [2]. With increasing health care costs and limited access to treatment, technology-enabled solutions—ranging from systems designed to support therapy to apps and websites focused on mental health and well-being self-management—offer an affordable and accessible alternative. A wide range of studies have explored the impact, benefits, and limitations of individual technology types. With 87% of adults in the United Kingdom [3] and 89% of adults in the United States [4] having access to the internet, the potential for Web-based mental health systems has been recognized for several decades.

In the context of treatment, structured Web-based programs, particularly computerized Cognitive Behavioral Therapy (CBT) targeting depression and anxiety, have been widely researched. Examples include Beating the Blues [5], MoodGYM [6], Big White Wall [7], and SilverCloud [8]. Web-based interventions address the need to widen the access to treatment and research suggests that they can be effective [9-12], but challenges remain. For example, they tend to have short-term effects [13] and only when supported by a therapist, rather than as stand-alone interventions [14,15]. Moreover, low uptake rates indicate lower acceptability than noncomputerized approaches [16]. Poor adherence has been reported for Beating the Blues and MoodGYM in real-world settings [14]. The use of generic content rather than targeted content and absence of human support can make Web-based interventions feel impersonal [9,17].

Complementing treatment-focused programs, people can also access many websites and Web-based materials that support self-management of common mental health issues. For example, SuperBetter [18] encourages people to complete tasks that help them take care of their mental well-being and provides interactive content to keep them motivated; an evaluation study conducted with 283 participants suggests that it could be effective at helping people manage their depression [19]. Headspace [20] is another example, focused specifically on mindfulness. Although caution is required and further research is needed to more rigorously validate its efficacy in supporting different mental health difficulties, initial research suggests that people have positive attitudes toward it and that it might be effective [21]; however, many find it difficult to fit the use into their routines [22].

Building on evidence that peer support can have a positive impact on people's mental health and well-being [23-25], Web-based peer support has become more common. Evidence suggests that the incorporation of moderated peer support can enhance Web-based treatment for early stage psychosis, with benefits including empowerment and increased social connectedness [26,27]. A study of 7Cups, a Web-based community focused specifically on mental health, provides preliminary evidence that people in emotional distress find support from trained nonprofessionals helpful [28]. More broadly, people can connect with others through general purpose social media sites, including Twitter and Facebook, and via discussion forums, such as Reddit, which has subreddits specifically focused on mental health issues. Evidence suggests people use these platforms to talk about mental health, as it gives them a sense of community, helps to raise awareness and fight stigma, provides a safe space for expression, and helps with coping and empowerment [29-31]. Although there is some research on the negative impact of social media on mental health, such as potential exacerbation of experiences associated with psychosis, mood disorders, and other mental illnesses [29], other studies suggest that social media is not a cause of mental health difficulty in and of itself [32], and that it can have positive impact in specific groups. For example, a case study by Veretilo and Billick [33] indicates that social networks may act as a springboard for greater societal integration, whereas Simoncic et al [34] suggest that Facebook use may be protective against depressive symptoms for female users with high levels of neuroticism.

Smartphone apps are the final category of technologies we address in this paper. Although social media and Web-based communities, such as Twitter or Facebook groups, are commonly accessed using smartphone apps, recent years have also witnessed a rapid increase in apps that specifically target mental health and well-being [35]. A number of recent systematic reviews and studies have analyzed the functionality offered by publicly available mental health apps [36-46], the context in which they are used and users' experience [44], how people discover and choose apps [47], and apps' grounding in theory [41-43,46]. Others have addressed the use of apps by specific population groups [48,49]. Although evidence suggests that a majority of publicly available apps are not grounded in theory, and this is a significant cause of concern, studies also suggest that appropriately designed apps can be effective in helping people address issues, including depression, stress, and anxiety [38,50,51].

Objectives

Taken together, the literature outlined above has allowed the research community to build an understanding of how people use different mental health technologies, identifying strengths, limitations, areas of concern, and recommendations for improvement. However, studies have tended to focus on a single type of technology, for example, apps or Web-based systems. In reality, individual technologies may not be used in isolation.

To build a more complete picture of the real-world technology use, this paper investigates which technologies (smartphone apps, discussion forums or social media, and websites or Web-based programs) people use to support their mental health and why, whether they combine multiple technologies and, if so, what purpose each serves, and which features they find the most valuable.

Methods

Study Design and Recruitment

We conducted an anonymous online survey to explore the use of different types of technology to support mental health and well-being. People were asked to participate if they currently used or had previously used apps, social media, or websites for this purpose. The survey was open from February 2017 to May 2017. We neither actively sought nor excluded people who were experiencing mental health problems at the time of the survey. To reach a wide range of participants likely to use technology, the survey was advertised on social networks (Twitter and Facebook, where we used snowball sampling [52] by requesting retweets and shares from both participants and nonparticipants) and via posters distributed at university. As an incentive for completing the study, participants were entered into a raffle with a chance to win one of several shopping vouchers: a £30 voucher, 1 of 3 £20 vouchers, or 1 of 5 £10 vouchers. The study was approved by the Faculty of Engineering Research Ethics Committee at the University of Bristol, project ID: 48021.

Survey Items

The survey comprised 59 questions, divided into 4 main sections: (1) the use of smartphone apps to support mental health and well-being, (2) the use of discussion forums or Web-based social networks to support mental well-being, (3) the use of websites or Web-based programs that offer support for mental well-being, and (4) background information about participants. In designing the survey, we recognized that technology categories used were not strictly exclusive, as, for example, it is not unusual for services like Reddit, Facebook, or Headspace to be accessed in multiple ways, including through a website or app. Our aim was to capture the use of broad categories of technology rather than specific products, while avoiding the creation of overly specific categories that would have resulted in an excessively long survey. For the purposes of this survey, we defined websites and Web-based programs that support mental health as sites that teach users skills and help them manage their well-being, for example, requiring more than a single visit and some input from the user. This includes websites that give users specific tasks to complete (eg, SuperBetter), Web-based programs that help to deal with stress or anxiety, support reflection on one's behavior, and help create action plans (eg, MoodGYM), or websites that help users do specific things (eg, meditation websites, such as Headspace). Questions from sections 1 to 3 covered usage patterns, frequently used features, engagement with technology, and suggestions for improvements. At the end of the survey, participants were also able to opt in for the voucher raffle and indicate their interest in receiving the summary of findings. We collected email addresses of those who opted in; they were stored separately from the survey data. Survey questions and full results are available in Multimedia Appendices 1-3.

Data Analysis

We used descriptive statistics to summarize general trends. In sections 1 to 3, survey respondents were able to provide suggestions for improvements and additional comments about each type of technology. We thematically coded these free-text comments and suggestions, and analyzed them together to identify wider themes spanning across all types of technology. The first round of coding was done by KS. Next, CP and DC reviewed the coding and added their own codes. Then, all authors discussed all codes and conducted affinity mapping [53], using Boardthing's collaborative Web-based board [54] to identify key themes. For open-ended questions asking about frequency of use, KS initially coded the responses, and other coauthors reviewed them and provided their own suggestions; we then counted the prevalence of each code and reported percentages.

Results

Demographics and Technology Use

In total, 102 people completed the survey. Although the survey was targeted at people who used technology to support mental health, 21 participants (20.5%) indicated that they did not use technology for this purpose, with the main reason being that it never occurred to them to do so, they did not need it, or because they would not feel comfortable using technology. These participants were excluded from further analyses, leaving 81 participants whose responses we analyzed (see Table 1 for their details).

A total of 52% (42/81) of the participants were women, and 66% (53/81) of the participants were aged under 35 years. A majority of eligible participants (64/81, 79%) reported receiving some sort of mental health or well-being support from a counselor, therapist, or health professional. Within this group, 67% (43/64) of the respondents provided optional details, which showed that they had received counseling (23 participants) and CBT (11 participants); 22 participants mentioned a mix of these and other approaches (eg, workshops or medications). Although 45% of the participants (36/81) reported combining multiple technologies, 56% (45/81) of the participants indicated using only 1 category. Smartphone apps were the most commonly used technology, with 40% of the participants (32/81) using only them. Furthermore, 38% (31/81) of the participants reported using apps in combination with other technologies. Only 1 participant reported using websites or Web-based programs in isolation, and 15% of the participants (12/81) reported combining all categories of technology surveyed. Key findings related to each technology type are described in the following sections. The first 3 subsections focus on closed survey questions related to smartphone apps, forums or social media, and websites or Web-based programs, respectively. Additional usage trends are available in Multimedia Appendices 1-3. Free-text responses are addressed separately, and the results of the thematic analysis are reported in the final Results section.

Table 1. Demographics of participants who reported using technology to support their mental health and well-being and the types of technology used (N=81).

Demographics and technology use	Participants, n (%)
Age (years)	
18-24	28 (35)
25-34	25 (31)
35-44	19 (24)
45-54	7 (9)
55-64	2 (3)
65-74	0 (0)
75+	0 (0)
Gender	
Female	42 (52)
Male	33 (41)
Nonbinary	3 (4)
Prefer not to say	3 (4)
Received professional mental health support	
Yes	64 (79)
No	15 (19)
Prefer not to say	2 (3)
Used only 1 type of technology	
Only smartphone apps	32 (40)
Only social media or forums	12 (15)
Only websites or Web-based programs	1 (1)
Used multiple types of technology	
Apps and social media or forums	9 (11)
Apps and websites or Web-based programs	10 (12)
Social media/forums and websites/Web-based programs	5 (6)
Apps and social media/forums and websites/Web-based programs	12 (15)

Use of Smartphone Apps to Support Mental Well-Being

A total of 78% of the participants (63/81) reported using smartphone apps to support their mental well-being, either at the time of the survey (41/81, 51%) or in the past (22/81, 27%). In this section, we describe key findings only; all survey responses describing usage trends of apps for mental health support are available in Multimedia Appendix 1. Participants most often mentioned Headspace, a mindfulness meditation app: its use was reported by 41% (26/63) of the participants. Calm, another app providing meditation and relaxation content, was mentioned by 8 participants. Moodscope, a mood tracker, was the third most popular, with mentions from 4 participants. Details of the remaining 8 apps (each mentioned by 2 or 3 participants) are available in Multimedia Appendix 4. The main reasons participants reported for starting to use the apps were personal recommendations by someone known to them (20/63, 32%) and finding the app in the app store (also 32%) or on the internet (17/63, 27%). Only 4 participants (6%) reported that a health professional recommended the app.

A majority of participants (36/63, 57%) reported that the apps they had used provided guided activities, such as meditation or breathing exercises, or helped with relaxation through imagery or calming music (21/63, 33% responses). Features that allow tracking various factors related to well-being, for example, mood, thoughts, and sleep patterns, were mentioned by a third of the participants (22/63, 35%). Unsurprisingly, the features that participants considered most important largely corresponded to the features they used most often. When asked to select up to 3 types of features most important to them, a majority of participants selected guided activities (37/63, 59%), recording and tracking information (25/63, 40%), and relaxation (20/63, 32%). Table 2 shows types of functionality available in the apps used by survey respondents (as reported by them) and the features they reported as being the most valuable.

Table 2. Types of functionality available in the apps described by survey respondents versus types of functionality they reported as the most important to them, sorted by importance. Respondents were able to select up to 3 most important features (N=63).

Functionality	Respondents reporting that these features were available in the app they used, n (%)	Respondents listing these features as most important, n (%)
Guided activities (eg, meditation, breathing exercises, and mindfulness)	36 (57)	37 (59)
Recording and tracking things (eg, mood, thoughts, sleep patterns, exercise, and activities)	22 (35)	25 (40)
Relaxation (eg, imagery, calming music)	21 (33)	20 (32)
Self-reflection and understanding (eg, through a journal or a behavior and thought analysis)	13 (21)	18 (29)
Advice or recommendations for activities	10 (16)	16 (25)
Setting goals and planning activities	11 (18)	13 (21)
Information about mental well-being and reading materials	12 (19)	10 (16)
Social features (eg, chat, forums, and discussion groups)	8 (13)	6 (10)
Other[a]	0 (0)	2 (3)
Games	0 (0)	1 (2)
Tests and quizzes	2 (3)	0 (0)

[a]Includes "not sure" and "ability to visualize issues."

Participants had an option to explain why they found these specific features the most important, and 68% (43/63) of them did so. Those who selected guided activities, such as meditation or breathing exercises, explained that these features helped them focus and deal with panic attacks, and they provided support "in the moment." They also allowed them to develop regular daily routines and practice new skills. Recording and tracking were valued by participants because they provided insights into patterns of behavior, helped to quantify moods, and generally helped to keep track of progress and assess whether their behavior was changing. Participants for whom relaxation features were important, valued their help in dealing with stress and calming down before sleep. Previous research has suggested that factors including customization, interactive features, peer support, and input from professionals may be important in supporting engagement with mental health technologies [55]. When asked about their attitudes to these types of features available in the apps, participants reported that all except peer support were important or very important to them (see Table 3).

A majority of participants reported using the apps at least once per week (43/63, 68%), with 32% (20/63) of the participants using them daily. Others reported using apps for a limited period (7/63, 11%), with frequency of use decreasing over time (4/63, 11%). A few participants (4/63, 11%) reported using the apps only when needed (eg, when stressed or unable to sleep). When asked how they remembered to use the app, 48% (30/63) of the participants said they did it in response to events or sensations (eg, to stop a panic attack or reduce anxiety). In addition, 29% (18/63) of the participants said it was a part of their daily routine, and 13% (8/63) of the participants reported using the app automatically; 32% (20/63) of the participants reported receiving reminders. Although a majority of the participants (41/63, 65%) reported using apps for more than 3 months at the time of survey, 35% (22/63) of the participants said that they had already stopped using them. The most common reason for abandoning the apps was getting bored (8/22 participants, 36%), finding a better way to support mental well-being (6/22, 27%), and not needing the app anymore (4/22, 18%).

Table 3. Respondents' attitudes toward aspects of smartphone apps that can influence engagement with technology (N=63).

Feature	Importance, n (%)				
	Very important	Important	Neither important nor unimportant	Unimportant	Very unimportant
Customization	19 (30)	28 (44)	10 (16)	3 (5)	3 (5)
Input from professionals	20 (32)	24 (38)	14 (22)	3 (5)	2 (3)
Peer support	8 (13)	6 (10)	13 (21)	24 (38)	12 (19)
Practical exercises	23 (37)	29 (46)	5 (8)	5 (8)	1 (2)
Self-monitoring	20 (32)	22 (35)	15 (24)	3 (5)	3 (5)

Use of Discussion Forums and Social Media to Support Mental Well-Being

A total of 47% of the participants (38/81) reported using discussion forums or social media. They most frequently mentioned Reddit (9/38, 24%) and Facebook (8/38, 21%). The full list of forums and social media sites mentioned by participants is available in Multimedia Appendix 4. Below, we summarize key findings; full findings are available in Multimedia Appendix 2.

Overall, when asked about the importance of being able to connect to others on the Web about factors that influence mental well-being, 61% (23/38) of the participants said it was important or very important. Participants reported using social media and discussion forums primarily to read other people's posts to learn more (32/38, 84%), help them understand their own situation (27/38, 71%), ask for advice (21/38, 55%), discuss problems and stressful situations (18/38, 47%), and give advice to others (18/38, 47%).

Among the survey participants who reported visiting discussion forums and social media to support their mental well-being, there were many who did so on a regular basis. A total of 29% (11/38) of the participants reported visiting them at least once a day, and 47% (18/38) of the participants reported visiting them at least once a week. A total of 24% (9/38) of the participants said they did it automatically, and 21% (8/38) of the participants said it was a part of their daily routine. Others reported doing so infrequently (4/38, 11%) or only when needed (6/38, 16%). Nearly half of the participants (17/38, 45%) reported that they logged in when they had a question or wanted to discuss something, and 42% (16/38) of the participants said they did that in response to events or sensations (eg, to stop a panic attack or reduce anxiety). A total of 66% of the participants (25/38) reported still using the discussion forums and social media at the time of the survey. Many participants also reported using discussion forums and social media over extended periods, with 58% (22/38) of the participants using them for over 6 months and 40% (15/38) of the participants using them for over 1 year. In contrast, 13 participants reported stopping using the site before the study, most commonly as they did not think they needed it anymore (6/13).

Use of Websites and Web-Based Programs to Support Mental Well-Being

A total of 35% (28/81) of the participants reported using websites and Web-based programs to support their mental well-being. However, it is important to note that only 1 participant used websites and Web-based programs in isolation, with all others using them in combination with apps or social media. A full list of websites and Web-based programs reported by the participants is available in Multimedia Appendix 4.

The sites mentioned most often were MoodGYM (5/28, 18%), Headspace (3/28, 11%), NHS Direct (2/28, 7%), and Big White Wall (2/28, 7%). Below, we describe the key findings; full usage trends are available in Multimedia Appendix 3. In total, 46% (13/28) of the participants who reported using a website or a Web-based program were still using the site at the time of the survey, whereas 54% (15/28) of the participants had stopped doing so. The most common reason for stopping was finding a better way to support their mental health (7/15, 47%) or not needing the site's support anymore (4/15, 27%). Regardless of whether they still used the sites, a majority of participants (20/28, 71%) reported using them primarily to find out how to deal with stress, anxiety, etc on a daily basis. Other reasons included wanting to develop specific skills (13/28, 46%), curiosity (9/28, 32%), recommendations from friends and family (7/28, 25%), and recommendations from health professionals (6/28, 21%). Participants reported using the sites either for a very short time, less than 4 weeks (12/28 respondents, 43%) or a prolonged period, over 12 months (9/28, 32%). A similar contrast was found in the follow-up question regarding frequency of use, with nearly a third of the participants (8/28, 29%) reporting using the sites once a month or less often, whereas 25% (7/28) of the participants reported doing it at least once per week. Where sites were used, it was often in response to events or sensations (14/28, 50%), although 18% (5/28) of the participants reported it was a part of their routine. When asked about engagement features available on the websites or Web-based programs they used, a majority of participants reported that practical exercises (24/28, 86%) and content created or endorsed by health professionals (23/28, 82%) were important to them (see Table 4).

Table 4. Respondents' attitudes toward features that can support engagement available on websites or Web-based programs (N=28).

Feature	Importance, n (%)				
	Very important	Important	Neither important nor unimportant	Unimportant	Very unimportant
Customization	6 (21)	13 (46)	5 (18)	4 (14)	0 (0)
Interactive features	6 (21)	9 (32)	8 (29)	5 (18)	0 (0)
Input from professionals	13 (46)	10 (36)	1 (4)	3 (11)	1 (4)
Practical exercises	14 (50)	10 (36)	3 (11)	0 (0)	1 (4)
Self-monitoring	6 (21)	14 (50)	3 (11)	3 (11)	2 (7)

Analysis of Open-Ended Comments and Suggestions for Improvements

Participants had the option to submit additional open comments about using each type of technology and suggest improvements. In total, 70% (57/81) of the participants provided such comments, which resulted in 119 open-ended responses that were coded and analyzed thematically. Through the analysis, we identified 4 themes reported below and discussed in more detail in the Discussion section. As one of the questions asked for suggestions for improvements, it is likely that participants took a critical perspective toward technology, with the emphasis on identifying limitations. This is reflected in the results.

Theme 1: Technology Can Support Targeted Activities, but It Is Not a Substitute for Face-to-Face Therapy

For some participants, technology, regardless of its type, wholly satisfied targeted aspects of their mental health needs. For example, a participant stated the following:

> *All I need is a mobile journaling tool with a search function that allows me to tag and store and later look up topics - so it's perfect really!* [P12]

The same person also appreciated the social network she frequently read:

> *The wonderful thing about the internet is that it's full of supportive communities of people with problems that are similar to yours. I believe that no problem is completely unique (there are always people in the same boat) and searching online helps me to find others who have the same problem, have figured it out and have shared it. I am more interested in hearing other people's solutions, perspectives and strategies for problems rather than ranting.* [P12]

In contrast, many participants had had face-to-face mental health treatments in the past and compared technology with this experience. The comparison was often negative, suggesting technology was a second-best option:

> *I ultimately found myself being more engaged with a therapist face to face - I felt like I was able to challenge and interrogate the actual therapy more.* [P97]

Some participants reported using technology as an alternative when traditional services were not available because of lack of time, access, or financial constraints:

> *I started using online services due to a recent lack of face-to-face support recently. I would prefer face-to-face in general, as I find it more stimulating and helpful.* [P22]

Frustration was noted when participants perceived that technology was being "pushed" inappropriately as a substitute for professional help, as a means to reduce costs. This highlights the fact that many participants did not see technology as a substitute for face-to-face treatment:

> *[Big White Wall] is really not a substitute for a good counsellor or support group (although it is being pushed as such by the university and by the NHS).* [P12]

Theme 2: People Want Personalized and Actionable Data

Participants highlighted the effectiveness of technology at supporting the acquisition of new habits, as well as their desire to be able to track various aspects of their behavior:

> *This to me was a great way to help me do some more meditation that I was trying to incorporate into my daily routine.* [P67]

Reminders are one of the features that could support this, but participants' reports highlighted mixed attitudes toward them and the need for more sophisticated support that leads to action:

> *Less reminders but more suggestions how to put it into a routine / when to use it.* [P10]

Customization was seen as valuable, but participants regularly wished for greater flexibility and targeted customization to ensure the information they gathered was more meaningful and personalized:

> *Change the mood tracking questions so that I can spot some variation in them. As it stood, I used the mood tracker for a while, but I always gave the same answers, so it wasn't worth the bother.* [P51]

There was also a strong desire that technology supports a more nuanced view of mental health:

> *Could take more account of grey areas when it comes to mental health. [...] Just cause [sic] I can do daily activities to some extent doesn't mean that I am having a good mental health day.* [P52]

As noted above, some participants had a tendency to contrast technology with face-to-face support, noting that face-to-face approaches provided greater flexibility:

> *Although there were personalised [sic] elements (eg setting your own goals), it didn't always cover what I needed to cover (things that were later teased out from face to face CBT).* [P97]

Finally, although many participants recognized the benefits of activities, such as tracking, there was a clear desire for technologies that could translate this into recommendations for actions that are concrete, targeted, and personalized:

> *I haven't come across any that seem to be effective, at least for me. Something combining tracking and action based specifically on the results of the tracking might be best.* [P61]

Theme 3: Trust is a Critical Factor Across Mental Health Technologies

The issue of trust came up on 3 different levels: trust in the system, trust in the content, and trust in the community. The lack of trust in the system (app, website, and forum or social network) was represented by users' concerns about privacy and security:

> *My primary concern would be around the use of the data I disclosed, not just by the company but potentially by other users in the future.* [P6]

Issues with trust in the content were represented by comments highlighting the need for more evidence-based materials or more input from professionals, which was related to reliability of information that was available or could be collected through technology:

> *There needs to be evidence! So many apps out there; don't want to waste my time on stuff that's rubbish or just out to make companies money - especially not when I'm feeling low.* [P81]

Another participant reported the following:

> *[I would like] more direct influence and response from experts, and having all the posts responded to by experts.* [P20]

Participants also raised issues with reliability of advice, the need for moderation, and concerns that unmoderated content may make things worse or be dangerous:

> *Useful when moderated. Access to mental health info/experiences of others on Tumblr/Twitter as a teenager served to make my health worse.* [P52]

Another participant said the following:

> *Often the people who are most ready to provide advice are not the best people to be giving that advice.* [P79]

Theme 4: Concerns About Overuse of Technology

Some survey respondents highlighted concerns toward technology in a general sense. For some, overuse of technology was seen as an issue in itself, and some people remarked that they simply did not want to use computers or apps more:

> *I feel somewhat uncomfortable with needing technology to look after my mental health. I probably spend too much time on my computer already.* [P22]

Other participants expressed feeling uncomfortable using mental health apps and reported that mental health technologies had the potential to exacerbate their condition:

> *The app itself did what it was supposed to - it just wasn't enough for me. I think on some level I hoped it would 'fix' my anxiety (ridiculous, I know) and when it (obviously) didn't, I began to associate the app with anxiety and seeing the icon on my phone made me worry about needing to use it.* [P4]

In some cases, these concerns were the reason for nonuse or discontinued use:

> *I am concerned about the addiction potential of smartphones and doubt that apps can support mental wellbeing. In my humble opinion mental wellbeing can even be reduced by using smartphones.* [P66]

Discussion

Principal Findings

Our findings show that people use different types of technology to support their mental health, and each can serve a distinct purpose: apps allow people to follow guided activities and monitor their health, social media and forums enable the discussion of issues with others and getting advice, whereas websites are a source of information about how to deal with issues on a day-to-day basis and help people develop specific skills. Smartphone apps were the most commonly used technology, but many people also mix and match different technologies. Irrespective of the type of technology, we found evidence that expectations can play a key role in people's experience of technology. Particularly, the attitudes toward technology can be negative if it is presented (or "pushed") as a replacement for face-to-face support. Technology can play an important role in supporting targeted activities, but to maximize this potential, participants indicated a desire for more nuanced and personalized technologies, which recognize the gray areas of mental health and help them plan informed actions. Trust is a key factor in people's attitudes toward technology. These issues are discussed in greater detail below and considered in relation to previous literature.

Expectations and the Role of Technology

In discussing key problems with current digital mental health research, Mohr et al [56] argue that it is a misconception to view mental health technologies as simply a new way of delivering traditional, evidence-based psychotherapy. They argue instead that technology has the potential to revolutionize mental health and open fundamentally new intervention models. Their argument is focused on the research community, but our data suggest that it can be extended to include people who use technologies to support their mental health. Many of our participants had past or current experience of face-to-face care. Our data suggest that those who viewed technology negatively often did so on the basis of comparisons with face-to-face psychotherapy. In some cases, people felt technology was being incorrectly "pushed" as a replacement for face-to-face treatment because of resource constraints in health care services. Frustration in this case is understandable. However, it might be addressed as part of a broader reframing of technology, where it is viewed not as a replacement for traditional services but as part of a new, broader ecosystem in which technology both complements and extends traditional approaches. In this framing, the expectations of technology are subtly different: it is no longer a second-best option; rather, it is a different option that offers people new opportunities to engage with their mental health. The onus for researchers then also shifts to understanding how technology can extend the overall mental health ecosystem, identifying the contexts and groups with whom different technologies are most effective, setting realistic expectations of technology, and communicating these new choices to end users. In this study, those who used technologies as an active choice—or used it as an adjunct to a traditional therapeutic relationship—had different expectations and a more positive experience of technology. Previous studies [9,57] also show that technology is viewed more positively when it matches the expectations of users and is an active choice. Viewed as a single option in an overall ecosystem, the choice to not use technology or limit its use will be a correct decision for some people. The challenge is to identify approaches that are effective and fit individual needs, irrespective of the medium.

Apps and Smartphones

Many participants in this study combined different technologies, but smartphone apps were clearly the most widely used technology, either in isolation or in combination with others. Given that smartphones are also a common access point for social media and Web-based services, they clearly represent a vital part of the ecosystem of mental health technologies. Our findings corroborate the results of recent work by Schueller et al [47], which focused specifically on app use. Features such as tracking, notifications, interactivity, and customization are identified as important in both studies. Privacy, again identified as important in both studies, is discussed in greater detail below. Personal recommendations were the leading factor in people's decision to use an app in both studies. Among our participants, only 6% of them were recommended an app by a health professional. This is lower than that reported by Schuller et al, but it is consistent with their finding that informal sources are currently more important than formal sources in identifying mental health apps. Interestingly, although the numbers in this study are too low to support strong conclusions, our findings indicate that health professionals in the United Kingdom are currently more likely to recommend Web-based resources than apps. It is possible that health professionals are less confident in the efficacy of apps, but it may also be because of institutional support from Web-based systems or a lack of awareness of available apps. Our evidence supports Schueller et al's recommendation for further engagement with health care providers to understand their needs and raise awareness of apps that are safe and efficacious.

Moving Toward Personalized and Actionable Recommendations

It is important to recognize that dropout is not unique to technology-based mental health. It is also high in traditional face-to-face approaches. To maximize engagement with mental health services, the challenge is to identify approaches that are effective and fit individual needs and preferences, irrespective of the medium. Our results suggest that the combined use of different technologies can serve many different needs, ranging from information provision and professional and peer support to tracking and targeted activities. A strength of digital technology, smartphones in particular, is its ubiquity and personal nature [58]. It means that users can access support in the moment, in response to feelings or circumstances, and engage with a therapeutic practice or material when needed. This availability also means that it has potential to support the establishment of habitual practices to benefit mental well-being [22,44], perhaps more so than traditional psychotherapy. However, our results point toward a key direction through which future technologies can enhance peoples' experience.

Many current technologies allow people to collect data or provide guided activities—features people appreciate—but most fall short in providing actionable data that lead to a positive change. This limitation has also been highlighted by other recent research [59-61]. Hollis et al [61] particularly emphasize the benefit of actionable analytics, where people are supported to reflect on both past and potential future selves and more constructively analyze their data to inform and plan actions that can support emotional well-being. In a similar vein, Rooksby et al [62] note that existing self-tracking features do not reflect the complex way in which people tend to monitor their health: they often interweave multiple data sources, share data with others, and have different needs depending on their short- or long-term goals. This is reflected in our participants' desire for technologies to provide a more nuanced view of mental health. Greater personalization and support for this more nuanced approach, linked to targeted, action-oriented recommendations, is a key challenge for future research. Promising initial work in this area has been carried out by Mohr et al [51,63], who developed IntelliCare: an eclectic suite of highly focused elemental apps that together provide a wide range of features, which can be combined and used as needed.

Trust and Validity

Trust is a founding principle of effective psychotherapy relationships. If future systems are to make more nuanced use of personal data and social features, trust will be a critical issue. The ability to access information and connect with others is a key strength of technology. It allows Web-based communities to form, where people can access and share personal stories and mutual support, when forming face-to-face versions would be difficult or impossible. Although participants recognized the value in this, they also shared concerns, including how and with whom data are shared, the need for evidence-based systems, and appropriate moderation. More broadly, this links to previously identified concerns about privacy [48], the unregulated nature of digital health technologies [64-66], and limited evidence-base of mental health apps [41-44,46], which can reduce trust in technology and lower user engagement [67]. Web-based information and advice—be it from peer support groups, websites, or services provided in apps—effectively come with an implicit warning, reduced trust. This in turn, even when the information or service is completely authentic, may erode people's confidence in the effectiveness of technology. Conversely, there is a danger that people may place unwarranted trust in technology that is labeled as being offered by a "professional." This is worrying, as systematic reviews of publicly available apps show that not all apps that mention the involvement of health professionals in their descriptions provide evidence-based features [44]. Schuller et al [47] argue that research is needed to help people identify valid, evidence-based, and trusted sources. Stawarz et al also argue that the responsibility in this area must extend beyond the research and regulatory bodies, with responsibility also resting with those who distribute technology, for example, app store owners [44].

Limitations and Future Work

The survey was advertised on social media and via posters on a university campus in the United Kingdom, which is likely to have attracted younger, more tech-savvy respondents. Although our survey software used cookies to reduce the likelihood of multiple responses by the same participant, we cannot guarantee this. We also specifically recruited people with experience of using technology to support their mental health. As such, our data cannot be taken to reflect the attitudes of the general public in regard to such technology. However, although this may limit the generalizability of our sample, it helped us attract participants who used multiple technologies, which offers insights into how they complement each other. Generalizability is also limited because of the size of the sample, but the fact that many of our results corroborate those of other recent research increases our confidence in our findings. Future work should explore this mixing and matching of technology in more detail, especially given that Millennials and future generations are growing up with technology, which will have an impact on the types of mental health support they may seek.

Conclusions

Our research suggests that although apps are the most widely used mental health technology, people also tend to combine different technologies to support their mental health. Each technology can serve a specific purpose. Participants valued social features and felt technology can support targeted activities, but they were also aware of the limitations of technology. Many compared it unfavorably with face-to-face therapy. Users want apps, social media, and websites providing mental health support to be more trustworthy, nuanced, and personalized; they want actionable data about their health and clear guidance. This is both a challenge and an opportunity, as the mix of technologies suggests people may not necessarily need an all-in-one solution. Therefore, future interventions should explore the use of multiple technologies and their combined effects on mental health support.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Supporting mental health with apps: usage trends.

[PDF File (Adobe PDF File), 82KB - mental_v6i7e12546_app1.pdf]

Multimedia Appendix 2

Supporting mental health with social media and discussion forums: usage trends.

[PDF File (Adobe PDF File), 83KB - mental_v6i7e12546_app2.pdf]

Multimedia Appendix 3

Supporting mental health with websites and Web-based programs: usage trends.

[PDF File (Adobe PDF File), 85KB - mental_v6i7e12546_app3.pdf]

Multimedia Appendix 4

Full list of apps, forums or social media, and websites or Web-based programs listed by survey respondents.

[XLSX File (Microsoft Excel File), 13KB - mental_v6i7e12546_app4.xlsx]

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Abbreviations

CBT: Cognitive Behavioral Therapy
NIHR: National Institute for Health Research

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Original Paper

Exploring Young People's Perceptions of the Effectiveness of Text-Based Online Counseling: Mixed Methods Pilot Study

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Abstract

Background: Young people aged 10-24 years are at the highest risk for mental health problems and are the least likely to seek professional treatment. Owing to this population's high consumption of internet content, electronic mental (e-mental) health services have increased globally, with an aim to address barriers to treatment. Many of these services use text-based online counseling (TBOC), which shows promising results in supporting young people but also greater variance in outcomes compared with adult comparators.

Objective: This pilot study qualitatively explored the characteristics of users aged 15-25 years accessing TBOC services, their motivations for access, and their perceptions about factors believed to influence the effectiveness of these modalities.

Methods: E-surveys were administered naturalistically to 100 young service users aged 15-25 years who accessed webchat and email counseling services via an Australian e-mental health service. Thematic analysis of qualitative themes and quantitative descriptive and proportional data presented in electronic surveys were examined across the areas of user characteristics, motivations for selecting TBOC modalities, and their perceptions of TBOC effectiveness.

Results: Participants were predominately female high school students of Caucasian or European descent from middle socioeconomic status, living with their parents in major cities. Four domains and various themes and subthemes were related to participants' reasons for accessing TBOC and perceptions of its effectiveness: user characteristics (ie, physical and mental health syndrome and perceived social difficulties), selection factors (ie, safety, avoidance motivation, accessibility, and expectation), factors perceived to increase effectiveness (ie, general therapeutic benefits, positive modality and service factors, and persisting with counseling to increase benefit), and factors perceived to decrease effectiveness (ie, negative modality and service factors, and persisting with counseling despite benefit).

Conclusions: Participants were motivated to use TBOC to increase their sense of safety in response to negative perceptions of their social skills and the response of the online counsellor to their presenting problem. By using TBOC services, they also sought to improve their access to mental health services that better met their expectations. Factors that increased effectiveness of TBOC were the counsellor's interpersonal skills, use of text-based communication, and persisting with beneficial counseling sessions. Factors that reduced TBOC effectiveness were poor timeliness in response to service requests, experiencing no change in their presenting problem, not knowing what postcounseling action to take, and persisting with ineffective counseling sessions.

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KEYWORDS

mental health; child health; adolescent health; distance counseling; mhealth; applied psychology; psychological processes

Introduction

Background

Population-based prevalence and cross-cultural studies indicate that young people aged 10-24 years are at the highest risk for developing emotional and mental health problems [1-8] and are also the least likely to seek professional treatment [9-14]. Since many mental health disorders become more serious over time [1,15,16] and can benefit from early treatment [17-19], the underutilization of mental health services by young people has sparked considerable academic interest [20].

Several barriers to mental health help seeking have been identified for young people including knowledge-based barriers related to mental health literacy and service awareness; structural barriers related to service accessibility and affordability; and sociocognitive barriers related to beliefs about the nature of mental ill health, how one should manage problems, and concerns about the help-seeking process [21-26]. Academic interest has therefore turned to internet-based interventions owing to the advantages in their cost-effectiveness and accessibility over conventional service delivery, which is believed to reduce the aforementioned barriers to care [27-29]. Consequently, a network of electronic mental (e-mental) health services has emerged in the international market, seeking to improve the accessibility of services to young people [30,31], many of which have been adopted into national mental health strategies [32-34].

Although face-to-face counseling remains the favored modality for most young people seeking mental health support [10], an increasing number have expressed a preference for text-based online counseling (TBOC) using asynchronous (eg, email, short message service [SMS], and forum) and synchronous (eg, webchat) modalities [35,36]. Literature examining the effectiveness of these modalities in supporting young people is in its relative infancy and shows mixed but generally promising findings [37-41]. In comparison with the adult e-mental health literature, these findings also appear to show relatively greater variance [42-47]. This raises important questions about the aspects of TBOC that may make it less effective for young people, which requires an understanding of the characteristics of young service users, their motivations for access, and their perception of factors that affect counseling outcome.

Despite the paucity of TBOC literature for supporting young people, existing research offers several useful insights. Studies indicate that the demographic background of young service users on TBOC modalities majorly (80%) comprises female-identifying 14- to 17-year-old adolescents from urban locations [40,48-51]. Some research also suggests that a significant proportion of young people using TBOC may be one-off service users [40,50,51] or accessing more than one mental health service [50]. Studies indicate that the motivations underpinning young people's selection of TBOC modalities center on perceptions of its heightened safety due to environmental privacy, anonymity, autonomy, control, and emotional distance from the counsellor as well as its increased accessibility due to its convenience, ease of access, and affordability [35,38,49,52-55]. Other motivations include a preference for text communication and polarized minimal or heightened expectations about the outcome of counseling [37,56,57]. Studies indicate that most common presenting problems for young people accessing TBOC are related to mental health, relationships, and information-related requests (eg, medico-legal questions, service referrals, and resource requests) [31,38,39,48,58], with some evidence suggesting that service users experience a higher level of distress or perceived burden of the problem than those presenting on telephone-based modalities [39,50,51]. Finally, at least one study found that young people perceived several obstacles to obtaining positive outcomes using TBOC, including online counsellors misunderstanding their content and emotions, difficulty capturing the online counsellor's mood, challenges building a therapeutic alliance, poor timeliness in responses to service requests, and not having enough time to work on a problem [49].

Several themes are striking with regard to factors that may explain the variance in TBOC effectiveness for young people. First, the user characteristics and motivations of young people suggest that many are early help seekers desiring safety or control over service use, which may indicate issues with readiness and motivation for change. Many young people also appear to have minimal or heightened expectations about counseling outcome while presenting with high distress or complex problems, which may indicate a poor fit between the complexity of presenting problems and what is possible at TBOC services, given their modality-specific limitations. Finally, young people appear to struggle with a number of service-modality factors common to TBOC services, such as building a therapeutic alliance in a text-based environment, poor timeliness in response to their service requests, and not having enough time to work on a problem. With the popularity of e-mental health services for young people across the globe, it is imperative to investigate the factors that increase and decrease the effectiveness of these services.

Objective

The primary aim of this study was to confirm the following domains and themes indicated by the literature about young service users' TBOC experiences for measurement in a larger future study:

- User characteristics (eg, age, gender, geographic location, and physical and mental health status)
- Motivations for selecting TBOC (eg, safety, accessibility, and expectation)
- Therapeutic benefits experienced during sessions (eg, catharsis and validation)
- Experiences of ineffectiveness (eg, not making any progress)
- Reasons for persisting with counseling when perceived to be ineffective

The secondary aim of this study was to expand on areas endorsed by participants in order to identify additional constructs of interest for our future study. It was expected that young service users would endorse each of the domains and themes being measured in line with the existing literature. Although similar literature exists, to our knowledge, no study has specifically investigated young people's perceptions about what decreases the effectiveness of TBOC services. It is believed that investigating effectiveness from this perspective will allow for a more in-depth analysis of what contributes to the variance in effectiveness observed in TBOC outcome literature.

Methods

Design

The study utilized a naturalistic mixed methods approach using electronic surveys (e-surveys) to collect data about young service users and their motivations and perceptions of TBOC effectiveness relative to face-to-face services, where applicable. It was reasoned that to naturalistically gather these data, while facilitating the well-documented desire for privacy and anonymity in this population, individual surveying techniques were best suited to this investigation [59].

E-surveys were informed by previous literature and were designed to confirm the aforementioned domains and themes by using four common steps:

- The presentation of information about a target TBOC domain
- Asking participants to rate whether they had ever experienced themes in this domain when utilizing TBOC services on a dichotomous Yes/No scale
- Asking participants that endorsed the target domain or themes to rate its significance to them on a 5-point Likert scale
- Asking participants that endorsed the target domain or themes to elaborate on their experiences, or to identify new related TBOC domain or themes

The full list of survey items can be found in Multimedia Appendix 1.

Participants

Participants were a naturalistic sample of 359 young Australians accessing *Kids Helpline*, a national e-mental health service in Australia for young people aged 5-25 years. Exclusion criteria in the study were age < 15 years and never having used TBOC at an e-mental health service, which resulted in 148 young people being disqualified from the study. Exclusion criteria were selected to improve the quality of responses by minimizing literacy issues associated with very young age and inexperience with using various TBOC services. A total of 107 participants who had substantial missing data (>50%) and four participants who had missing data related to the core construct measurement had their data removed from the analyses.

Procedure

Ethical approval for the present study was obtained from the University of Queensland's Behavioural & Social Sciences Ethical Review Committee. Participants were recruited via an advertisement in the "virtual waiting room" of the webchat counseling service or in the footer of emails exchanged between user and counsellor as part of the email counseling service. Participants were asked to complete an e-survey hosted external to the service (ie, Survey Gizmo). Participant responses were downloaded by researchers directly from the e-survey software.

Data Analysis

Descriptive statistics and thematic analysis (ie, deductive and inductive) were the primary approaches for understanding patterns and themes in participants' perceptions about the effectiveness of TBOC. According to Braun and Clarke [60], thematic analysis typically involves the process of becoming familiar with data, generating initial thematic codes, searching for themes, reviewing themes, defining and naming themes, and producing a report. Descriptive statistics that informed deductive themes were calculated within the e-survey software. Qualitative data were analyzed manually by the primary author who identified and defined a set of preliminary themes. A second independent researcher engaged in the same analytic process, and coding discrepancies 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 discussed. The final stages of analysis involved the authors reviewing themes and subthemes to ensure that coded extracts were valid, logical, and reasoned.

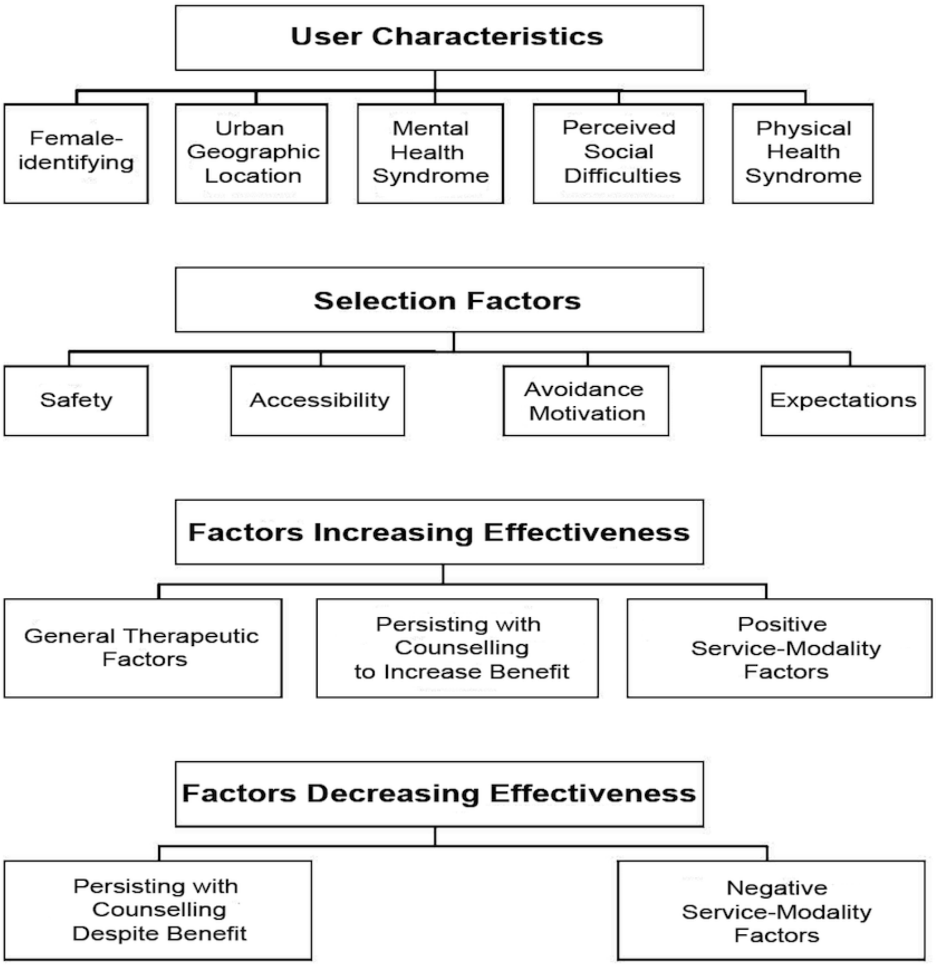
The magnitude of themes was rated as *very strong*, *strong*, *moderate*, and *weak* if >80%, >50%, >30%, >10% of participants offering quantitative (N=100) or qualitative (N=70) data endorsed the theme, respectively, with cut-offs drawn from the effect size literature. Quantitative ratings of *very important* and *important* were aggregated. Where frequency data for a theme existed quantitatively and qualitatively, the highest percentage was assigned a magnitude rating and a percentage range. Themes endorsed by fewer than 10% of all participants were excluded from the analysis on the grounds of low generality.

Results

Overview

Four domains were confirmed to be related to participants' user characteristics, their motivations for selecting TBOC, and their perceptions of its effectiveness: *user characteristics*, *selection factors*, *factors perceived to increase effectiveness*, and *factors perceived to decrease effectiveness*. Figure 1 shows an illustrative overview of primary domains and themes identified in the study.

Figure 1. Nonhierarchical overview of primary domains and themes identified in the study.



User Characteristics

Participants confirmed three themes related to their *user characteristics*: *gender*, *geographic location*, and *mental and physical health status*. A fourth theme, *perceived social difficulties*, emerged from participant qualitative data. An overview of the themes related to the *user characteristics* domain can be found in Table 1.

The final sample consisted of 100 participants aged between 15 and 25 years (mean 19.6, SD 3.2). Of this number, 81 were female, 64 were of Caucasian or European descent, 59 followed no religion, and 76 were not in a committed relationship. Sixty-seven participants identified their primary vocational role as a student, and 71 participants were in high school or had a partial high school education. In addition, 57 participants were living with both parents. Most participants were also accessing the services from major Australian cities, with 28 living in New South Wales, 24 living in Victoria, and 22 living in Queensland. More than half the sample was estimated to be from a middle socioeconomic status based on parental education proxy indicators, where 58 and 59 participants had one or two parents, respectively, who had completed schooling below university level. Eighty-eight participants reported using the noncall and internet features of their devices on a daily or near-daily basis. Seventy participants had used webchat counseling previously, 23 participants had used both webchat and email counseling previously, and 7 participants had only ever used email counseling. Participants also had a mix of experience using webchat or email counseling, with 41 having used these services 2-4 times, 32 having used these services 4-10 times, and 27 having used these services ≥10 times. There were no demographic differences between participants who provided qualitative responses (n=70) and those who did not, with the exception of fewer responses from short- and long-term users.

About less than half of the sample (46/100) reported having been diagnosed with a *mental health syndrome*. The most common mental health syndromes were anxiety (35/100) and mood (30/100) syndromes, followed by personality (12/100), posttraumatic stress (11/100), and eating syndromes (10/100). Twelve participants reported having been diagnosed with a chronic *physical health syndrome*. The most common physical health syndromes were respiratory disease (5/100) and other nonspecified diseases (5/100).

Having perceived social difficulties that made it challenging to access nontext counseling modalities emerged as a qualitative theme (17/70, 24% of participants). Participant responses were variable. Key aspects that emerged were anxiety and fear when communicating verbally, a perceived deficit in communication skills, and a lack of confidence with verbal communication.

Table 1. Overview of the themes related to the *user characteristics* domain that were confirmed and identified in the study.

Themes	Strength	Examples
Female-identifying gender	Very strong	—[a]
Urban geographic location	Strong	—
Mental health syndrome	Moderate	—
Perceived social difficulties	Moderate	"It's hard for me to open up to people because I don't know how to start the conversation with somebody face to face, especially because I'm an awkward and occasionally shy person"
Physical health syndrome	Weak	—

[a]Not available.

Table 2. Overview of themes and subthemes related to the *selection factors* domain that were confirmed and identified in the study.

Themes and subthemes	Strength	Examples
Safety	Very strong	
Increased privacy	Very strong	"Privacy is important to me because I reallyyyy do not want my parents to know... well, anything", "It's difficult to have a phone conversation about delicate matters when others are around but no one can over hear a web chat"
Facilitates honesty or communication of sensitive issues	Very strong	"I can talk about things I would otherwise be too scared to talk about like past sexual abuse"
Increased anonymity	Strong	"I feel in control of things better being anonymous it's easier to chat about hard things"
Reducing the emotional intensity of conversation	Strong	"Less confronting, as phone calls I find hard to deal with and I feel less self-conscious on a webchat"
Increasing control and autonomy	Strong	"I needed to feel like I could control the conversation, like I could say whatever I wanted and not feel judged"
Avoidance motivation	Strong	
Being overheard or seen attending a service	Moderate	"I did not want my family to find out that I needed to talk to someone. as far as they were concerned I was happy"
Social interaction	Weak	"I don't really like talking to people or people who help so I found the online service very helpful. They could still get an idea of your issue but you didn't have to go back or be face to face"
Minimize intense Or difficult emotions	Weak	"Because I get teary easily and I don't like crying whilst trying to talk to someone"
Counsellor reaction	Weak	"It's so much easier to talk o counsellors online or via email because they don't know who you are, don't know who you look like, how you act etc. So they can't exactly judge you on things like that, that some people find are important"
Accessibility	Strong	
Convenience and flexibility	Strong	"I can come on at any time when I feel I need to, rather than wait for the appointment with another counsellor face to face"
Faster access to counseling	Strong	"Because I become in need of support very suddenly often when I am alone, so this means I can access support immediately"
Affordability	Strong	"I am very young and have no way of getting to or paying for face-to-face counseling"
Counseling in areas of low service Density	Weak	"Where I live, there isn't any services such as a therapist"
Source one's own counseling support	Weak	"I was restricted in a way meaning that I wasn't able to be taken somewhere to see a councillor [sic] so this was the only way I was able to access help"
Expectations	Strong	
Help with low complexity issue	Moderate	—[a]
More helpful than other services	Moderate	—
Comparable to other services	Moderate	"I think that online counseling is just as helpful compared to face to face counseling and that's important to me because usually during the week, because of school, I don't have time be taken to see a counsellor face to face".
Help with high complexity issues	Moderate	—
Self-responsibility or realistic expectations	Weak	"It can be helpful to talk to people but sometimes, it's only up to yourself to fix yourself. Nobody can help you, and although it can be a bit depressing and overwhelming thinking about that, it's true"

[a]Not available.

Selection Factors

Participants confirmed three themes related to their motivations for selecting TBOC for support: *safety*, *accessibility*, and *expectations*. A fourth theme, *avoidance motivation*, emerged from participant qualitative data. An overview of themes and subthemes related to the *selection factors* domain can be found in Table 2.

Safety

A majority of participants (94/100) quantitatively confirmed that the perceived safety of TBOC services was a motivator for its selection over conventional counseling services. The importance of this theme was also qualitatively described by 74% (52/70) of participants. Five subthemes were identified within the *safety* theme.

The view that TBOC felt safer due to *increased privacy* resulting from using text-based communication was quantitatively endorsed by 82% (82/100) of participants and qualitatively described by 26% (18/70) of participants. Participant responses were similar. The key aspect described was the participant's desire to conceal details of their personal lives from those in their immediate environment, mostly parents.

The view that TBOC facilitated *honesty or communication of sensitive issues* with online counsellors due to its perceived safety was quantitatively endorsed by 82% (82/100) of participants and qualitatively described by 11% (8/70) of participants. Participant responses were similar. The key aspect described was the ability to discuss sensitive issues they might not have otherwise disclosed due to perceived *privacy*, *reduced emotional intensity of conversation*, and concealment of *counsellor reaction*.

Having increased *anonymity* from online counsellors due to the concealment of one's personal identity and location that increased one's sense of safety was quantitatively endorsed by 67% (67/100) of participants and qualitatively described by 22% (16/70) of participants. Participant responses were variable. Key aspects that emerged were about feeling safer, more comfortable, and in control during TBOC sessions and evading identification when discussing risk-related situations that the online counsellor may have a responsibility to report to authorities.

The perception that TBOC *reduced the emotional intensity of conversation* with online counsellors was quantitatively endorsed by 72% (72/100) of participants and qualitatively described by 4% (3/70) of participants. Participant responses were similar. The key aspect described was the benefit of feeling less overwhelmed when using text rather than verbal communication.

The perception that TBOC provided *increased control and autonomy* over various aspects of the counseling process was quantitatively endorsed by 56% (56/100) of participants and qualitatively described by 44% (31/70) of participants. Participant responses were variable. Key aspects that emerged were about *control* over the counseling process and *counsellor reactions* to increase one's sense of safety in sessions and *autonomy* in accessing a mental health service, especially where parental gatekeeping was a barrier.

Avoidance Motivation

A parallel theme that emerged alongside the perceived *safety* of TBOC was participants' underlying *avoidance motivation* for desiring the aforementioned benefits in the first place. This theme was qualitatively described by 64% (45/7) of participants. Four subthemes were identified within the *avoidance motivation* theme.

Selecting TBOC to avoid *being overheard* or *seen attending a service* was qualitatively described by 30% (21/70) of participants. Participant responses were similar. The key aspect described was the fear of being discovered while accessing a counseling service due to its social consequences, mostly from one's parents.

Selecting TBOC to avoid verbal *social interaction* with a counsellor was qualitatively described by 21% (15/70) of participants. Participant responses were similar. The key aspect described was the motivation to avoid discomfort and fear associated with verbal communication.

Selecting TBOC to *minimize difficult emotions* felt during the process of counseling was qualitatively described by 17% (12/70) of participants. Participant responses were similar. The key aspect described was about text-based communication feeling less emotionally intense than verbal communication, which reduced the risk of becoming overwhelmed in a session when discussing upsetting content.

Selecting TBOC to minimize a counsellor's potentially threatening reaction, such as judgment, in response to personal disclosures was qualitatively described by 15% (11/70) of participants. Participant responses were variable. Key aspects that emerged were about wanting to conceal judgmental reactions from the online counsellor and to circumvent other challenging reactions from the online counsellor (eg, misgendering).

Accessibility

A majority of participants (74/100) quantitatively confirmed that the *accessibility* of TBOC services motivated its selection over conventional counseling services. The importance of this theme was also qualitatively described by 60% (42/70) of participants. Six subthemes were identified within the *accessibility* theme.

The *convenience* of accessing TBOC was quantitatively endorsed by 66% (66/100) of participants. The *flexibility* in accessing TBOC was quantitatively endorsed by 57% (57/100) of participants and qualitatively described by 28% (20/70) of participants. Both subthemes were determined to be thematically interrelated by analysts because of construct similarity and coding of the subthemes together the majority of the time. Participant responses were variable. Key aspects that emerged were the convenience of access using one's own device and the flexibility of access from any location or at any time of day.

The *faster access to counseling* possible with TBOC services was quantitatively endorsed by 60% (60/100) of participants and qualitatively described by 17% (12/70) of participants (17%). Participant responses were similar. The key aspect described was the benefit of being able to access support at the moment of distress or crisis instead of having to wait for a face-to-face counseling appointment.

The *affordability* of TBOC was quantitatively endorsed by 51% (51/100) of participants and qualitatively described by 17% (12/70) of participants. Participant responses were similar. The key aspect described the benefit of free services due to financial barriers young people experience to accessing paid counseling services.

The manner in which TBOC improved access to *counseling in areas of low service density* was quantitatively endorsed by

20% (20/100) of participants and qualitatively described by 4% (3/70) of participants. Participant responses were variable. Key aspects that emerged were the scarcity of counseling services where participants live and the long distance to the nearest counseling service.

The ability to *source one's own counseling support* was qualitatively described by 11% (8/70) of participants. Participant responses were variable. Key aspects were about being able to manage one's own mental health care and overcoming (mostly parental) gatekeeper-related obstacles to mental health care.

Expectations of counseling

A majority of participants (53/100) confirmed *expectations about counseling* as a motivator for using TBOC services. The importance of this theme was also qualitatively described by 20% (14/70) of participants. Five subthemes were identified within the *expectations* theme.

Expectations that TBOC would *help with low complexity issues* (evaluated by a proxy question inquiring about "short-term issues") was quantitatively endorsed by 41% (41/100) of participants.

Expectations that TBOC was *more helpful than other services* used previously was quantitatively endorsed by 37% (37/100) of participants.

Expectations that TBOC services would be *comparable to other services* in effectiveness was quantitatively endorsed by 36% (36/100) of participants and qualitatively described by 4% (3/70) of participants. Participant responses were similar. The key aspect described was the belief that all modalities of counseling were comparably effective.

Expectations that TBOC would *help with high complexity issues* (evaluated by a proxy question inquiring about "long-term issues") was quantitatively endorsed by 31% (31/100) of participants.

Having self-responsibility over one's process of change in counseling or *realistic expectations* of what TBOC was able to offer was qualitatively described by 17% (12/70) of participants. Participant responses were variable. Key aspects that emerged were having no *expectation* that the online counsellor could help them and believing it was their own responsibility to create change in their lives.

Factors Perceived to Increase Effectiveness

Participants confirmed three themes related to perceptions about factors that increased the effectiveness of TBOC: *general therapeutic benefits*, *persisting with counseling to increase benefit*, and *efficacious modality and service factors*. An overview of themes and subthemes related to the *factors perceived to increase effectiveness* domain can be found in Table 3.

Table 3. Overview of themes and subthemes related to the *factors perceived to increase effectiveness* domain that were confirmed and identified in the study.

Themes and subthemes	Strength	Examples
General therapeutic benefits	Strong	
Feeling heard and understood	Strong	"The feeling of someone listening and understanding you helps you feel like you're not invisible"
Catharsis or debriefing	Strong	"To finally be able to talk about something I haven't been to talk about with anyone else and have even kept it from the professionals I see is very relieving"
Feeling normalized and validated	Strong	"I felt very safe and calm when I was talking to them because they made me feel important and like I was worth listening to no matter how big or small my problem was"
Rapport and feeling supported	Moderate	"It was really good to feel like someone was interested in what I was saying and cared about helping me"
Outsider perspective and support	Weak	"It felt good to speak to someone who doesn't actually know you as they can't judge you on what you speak about. They also offer and insight that I might not have thought of".
Problem clarification	Weak	"by talking to [online counsellors] I could understand my haywire emotions".
Persisting with counseling to increase benefit	Strong	"After a while I guess it does feel like the problems aren't solved but they do get better with more and more chats."
Positive modality and service factors	Moderate	
Facilitating expression and thought organization	Weak	"Because I get anxious talking to someone face to face and usually forget everything that I am feeling or that I am going to say but when I can type it out and think about what I'm saying"

General Therapeutic Benefits

A majority of participants (79/100) quantitatively confirmed that *general therapeutic benefits* were related to the effectiveness of the counseling process. The importance of this theme was also qualitatively described by 65% (46/70) of participants. Seven subthemes were identified within the *general therapeutic factors* theme.

Feeling heard (ie, "Being listened to") was quantitatively endorsed by 77% (77/100) of participants. *Feeling understood* was quantitatively endorsed by 72% (72/100). Due to the overlap between participant's qualitative descriptions of feeling "listened to" and "understood," both were collapsed into a single subtheme. The effectiveness of both *feeling heard and understood* by their online counsellor was qualitatively described by 24% (17/70) of participants. Participant responses were variable. Key aspects that emerged were facilitating engagement with the counsellor, helping them feel comfortable, helping them feel affirmed, reducing their sense of invisibility, and reducing their sense of being alone in the session.

The effectiveness of *catharsis or debriefing* was quantitatively endorsed by 64% (64/100) of participants and qualitatively described by 21% (15/70) of participants. Participant responses were similar. The key aspect described the benefit of debriefing one's personal situation with an online counsellor or feeling relief from doing so.

The effectiveness of *feeling normalized and validated* was quantitatively endorsed by 61% (61/100) of participants and qualitatively described by 8% (6/70) of participants. Participant responses were variable. Key aspects that emerged were about feeling accepted by the online counsellor, less alone with problems they were facing, and that their experiences were taken seriously.

The effectiveness of *rapport and feeling supported* was qualitatively described by 34% (24/70) of participants. Participant responses were similar. The key aspect described the benefit of feeling like the online counsellor cared about them and showed interest in helping them.

The effectiveness of *outsider perspective and support* was qualitatively described by 15% (11/70) of participants. Participant responses were similar. The key aspect described was the benefit of talking to a person outside of one's social network with an objective perspective about their presenting problem.

Perceiving the process of *problem clarification* via TBOC to contribute to its effectiveness was qualitatively described by 11% (8/70) of participants. Participant responses were similar. The key aspect described was the benefit of being assisted to better understand their presenting problems.

Persisting With Counseling to Increase Benefit

A majority of participants (56/100) quantitatively confirmed benefits associated with accessing TBOC over multiple sessions. The importance of this theme was also qualitatively described by 47.1% (33/70) of participants. Participant responses were variable. Key aspects that emerged were about persisting with contact due to benefits of *general therapeutic factors*, short-term benefits such as distraction and crisis-based support, and the belief that more sessions were associated with greater improvement.

Positive Modality and Service Factors

Factors perceived to increase effectiveness related to TBOC as a service and modality were confirmed by 47% (33/70) of participants. Six themes were identified within the *factors perceived to increase effectiveness* domain.

Perceiving that text communication was effective in *facilitating expression and thought organization* was qualitatively described by 14% (10/70) of participants. Participant responses were variable. Key aspects that emerged were the ease in articulating one's ideas compared to verbal communication and the better ability to organize one's thoughts in sessions.

Factors Perceived to Decrease Effectiveness

Participants confirmed two themes related to perceptions about what decreased the effectiveness of TBOC: *persisting with counseling despite benefit* and *negative modality and service factors*. An overview of themes and subthemes related to the *factors perceived to decrease effectiveness* domain can be found in Table 4.

Table 4. Overview of themes and subthemes related to the *factors perceived to decrease effectiveness* domain that were confirmed and identified in the study.

Themes and subthemes	Strength	Examples
Persisting with counseling despite benefit	Strong	"After talking to them for like the 10 time I didn't seem to feel much better than when I started talking"
Negative modality and service factors	Strong	
Problem not improving or ineffective techniques	Weak	"they wouldn't give me any real advice or opinion on my topic..."
Poor timeliness of response	Weak	"the only unhelpful thing is that often you guys are overly busy and not always able to connect with people"
Poor conversation of counseling into postsession action	Weak	"Even though I had discussed the problem I found it hard to make an action after the session to help solve the problem"

Persisting With Counseling Despite Benefit

A majority of participants (53/100) quantitatively confirmed that they continued to use TBOC despite substantial progress in resolving their presenting problem. This theme was also qualitatively described by 47.1% (33/70) of participants. Key aspects that emerged were about persisting with contact due to the inability to overcome chronic presenting problems such as mental ill health, realizing the short-term benefits of counseling had failed to produce long-term outcomes, dissatisfaction with one's *problem not improving* or *ineffective techniques* and a *poor conversation of counseling into post-session action*, and the belief that multiple sessions might be associated with greater improvement.

Negative Modality and Service Factors

A majority of participants (53/100) quantitatively confirmed *negative modality* and *service factors* as a theme comprised of themes related to difficulties making progress toward resolving a presenting problem. Four subthemes were identified within this theme.

Perceiving the effectiveness of TBOC to be lower due to a participant's *problem not improving* or *ineffective techniques* being utilized was qualitatively described by 18% (13/70) of participants. Participant responses were variable. Key aspects were TBOC generally not helping them resolve their presenting problem to a satisfactory degree and the experience of initially "feeling better" followed by the observation that the effects were not sustained.

Perceiving the effectiveness of TBOC to be lower due to the *poor timeliness of response* to a participant's session request was qualitatively described by 14% (10/70) of the participants. Participant responses were variable. Key aspects were negative feelings about having to wait for long periods to talk to an online counsellor and suggestions for service improvements to allow participants to make a more informed decision about whether to continue waiting during long queues or abandon one's efforts (eg, queue position indicator).

Perceiving the effectiveness of TBOC to be lower due to a *poor conversation of counseling into post-session action* was qualitatively described by 10% (7/70) of participants. Participant responses were similar. The key aspect described was about not knowing or having discussed with the online counsellor about what postsession action would help them progress toward resolving their presenting problem.

Discussion

Principal Findings

The aims of this study were to confirm and expand on domains and themes related to the characteristics of young service users accessing TBOC services and their motivations and perceptions of TBOC effectiveness.

In terms of *user characteristics*, demographic data confirmed that female-identifying participants living in urban areas made up the majority of the sample. This is in line with the literature suggesting that women comprise the majority of western service users and are believed to access TBOC in greater numbers due to its greater safety and accessibility [40,48-51]. Diagnosis with a *mental or physical health* syndrome was also highlighted, consistent with previous research [31,38,39,48,58] and Australian prevalence estimates [61]. Interestingly, there was a higher proportion of personality, posttraumatic stress, and eating syndromes than expected in the sample. However, this was in line with the observations of online counsellors in research [62,63] and may reflect the higher patterns of distress and problem burden reported by young service users on these modalities [39,50,51]. Uniquely, a quarter of participants reported *perceived social difficulties* as underpinning their selection of TBOC services. Although young people's preference for text-based communication is widely established in e-mental health literature, it is often attributed to cultural or technology preferences rather than anxieties about one's social abilities [53-55]. This finding may contextualize various dimensions of TBOC use regarding user characteristics (eg, anxiety presentations), selection motivations (eg, safety and avoidance), and factors perceived to moderate effectiveness (eg, facilitating expression and thought organization). However, as some participants reported developmental (7/100) and learning syndromes (5/100), further research is required to clarify factors that influence these perceived difficulties.

In terms of *selection factors*, participants confirmed *safety* and its subthemes as the strongest motivators for accessing TBOC services, consistent with e-mental health literature [30,36,49,53]. Similarly, participants confirmed *accessibility* as a strong motivator for selecting TBOC services with subthemes that mirror research about the aspects of these services that help young service users overcome financial, gatekeeper, and transportation barriers to mental health care [9,10,64,65]. Surprisingly, the advantages TBOC offers in providing *counseling in areas of low service density* and *sourcing one's own counseling support* were weaker themes. One possible explanation is that campaigning, resourcing, and servicing efforts in youth mental health have increased access to services such that they are not considered to be as important as they once were. *Expectations of counseling* were confirmed as another strong motivator for accessing TBOC services, in which participants described a dichotomy of subthemes about holding low-high expectations of the outcome of counseling. This too is consistent with the existing literature describing how young service users often do not know what to expect from e-mental health services or how they hold very high expectations of them [37,56]. Lastly, *avoidance motivation* emerged as a unique and strong motivator for participants in accessing TBOC services, with subthemes that paralleled and provided context for a participant's desire for *safety* factors. Interestingly, these subthemes were reported with much weaker strength than their *safety* counterparts, possibly pointing to nuanced differences between idealized and nonnegotiable aspects of service selection. Another possibility is that this theme was underreported due to measurement limitations in comparing quantitative (*safety* factors) with qualitative (*avoidance motivation* factors) data.

In terms of *factors perceived to increase effectiveness*, *general therapeutic benefits* were confirmed as a strong theme, with subthemes indicating the importance that participants place on interpersonal and relational aspects of the counseling process. These results are novel in their specificity about the *general therapeutic benefits* young service users find most helpful when working in TBOC environments, especially *problem clarification*, which has been associated with improved outcome in at least one study [40]. They are also unsurprising in view of the link between therapeutic alliance and outcome in working with young people via e-mental health services [66] and the fact that person-centered psychotherapy is one of the most common approaches to counseling at youth-focused helplines [67]. In contrast, *efficacious modality* and *service factors* were focused on the modality *facilitating expression* and *thought organization* in discussing a participant's presenting problems. The substantially lower strength of this theme was surprising, given its emphasis in the literature [53-55]. Nevertheless, this may reflect participants' perceptions of what works for their unique presenting problem, which may have resulted in a diversity of suggestions with little overlap. *Persisting with counseling to increase benefit* was also confirmed by participants as a means to increase the effectiveness of support, in line with research indicating that multiple sessions of TBOC are superior to single sessions [50]. Findings suggest that a positive feedback loop of *factors perceived to increase effectiveness* may contribute to young service user's persisting behavior. Nevertheless, further research is required to determine whether other factors may also encourage young service users to attend multiple TBOC sessions (eg, psychoeducation and help-seeking beliefs).

Finally, *factors perceived to decrease effectiveness* was confirmed as a strong domain with two themes. *Persisting with counseling despite benefit* was confirmed to be a strong theme, for which participants described experiencing various *factors perceived to decrease effectiveness* during TBOC sessions. This is an interesting finding that raises important questions about the reasons why young service users might persist using TBOC services when they are perceived to be of insufficient benefit. One possibility is that young service users may experience challenges in identifying or taking action about their declining treatment progress with online counsellors, resulting in repeated session attendance until the disadvantages of unproductive sessions become more apparent. This would be a valuable area of future research, given the increased probability of dropout likely from continued service ineffectiveness, which has been described as a contributing factor to the high dropout rates observed in e-mental health effectiveness research [68,69]. *Negative modality* and *service factors* produced three themes. Herein, *poor timeliness of response* appears to be a common complaint made by young service users about TBOC services [49], which may point to the unmet need resulting from low staffing relative to high demand. *Problems not improving* or *ineffective techniques* has also been inferred as an issue in TBOC process literature from the perspective of online counsellors in relation to modality-specific issues, such as heightened client anonymity, limitations in text-only communication, and the slow pace of typed sessions [62,63,70]. Finally, the *poor conversion of counseling into postsession action* was a unique finding in view of the fact that action planning processes are commonly utilized techniques by online counsellors [40]. Our findings may suggest that other factors complicate action planning for online counsellors, such as the aforementioned modality-specific limitations combined with a disproportionate amount of time spent building rapport and clarifying problems [40,62].

Implications for Online Counsellors

Our findings have several implications for youth-focused TBOC service model development and online counsellor training. First, awareness of common user characteristics and motivations for accessing TBOC services may help online counsellors better understand young service users' presenting problems and determine the best clinical course during sessions. Additionally, awareness of the *avoidance motivations* underlying a young service users' desire for *safety*, *accessibility*, and *expectations of counseling* may provide online counsellors with important insight that helps guide their selection of specific counseling interventions to use on TBOC modalities. For example, there may be an iatrogenic effect for young service users selecting TBOC services to compensate for perceived social deficits and an important role for employing exposure interventions that aim to collaboratively transition to verbal communication modalities. Finally, an awareness of *factors that increase and decrease effectiveness* of TBOC services has important implications for an online counsellor's therapeutic process. Our findings suggest that young service users may benefit from a combined *humanistic and solution*-focused counseling approach that balances supportive and problem-solving interventions as well as the incorporation of progress-monitoring practices to detect early markers of treatment ineffectiveness that lead to dropout. Additionally, busy TBOC service providers may benefit from software that provides feedback to young service users about their expected waiting time before speaking to an online counsellor, to help users make an informed decision about waiting in long queues or abandoning their efforts.

Limitations

There are three main limitations to this study that may affect the generality of the findings. First, although many findings were consistent with those in the existing literature, the sample was small and consisted of self-selected female participants above the age of 15 years, whose perceptions of TBOC may not align with the concerns of other genders or age cohorts. Further research is required to confirm the validity and generality of the reported domains and themes. The absence of comparator modalities (eg, SMS, forums, and social media groups) and relatively lower proportion of email counseling users also limits the conclusions that can be drawn about the generality of TBOC domains and themes. Having nontext–based e-mental health comparators would add further validity as well as a form of manipulation check to our findings. Finally, quantitatively measured domains and themes may have been overrepresented due to the lower effort required to respond to them as compared to drafting a qualitative response. Therefore, further research to confirm the validity of qualitative-only themes (eg, *factors perceived to increase and decrease effectiveness*) would be important.

Conclusions

This study examined the user characteristics and motivations of young service users accessing TBOC services and their perceptions about factors influencing its effectiveness. The study found that many participants selected TBOC services to increase their sense of safety in response to negative perceptions of their social skills and the online counsellor's response to their presenting problem. By using such services, they also sought to improve their accessibility to mental health services that better met their expectations. Factors that increased effectiveness of TBOC were the counsellor's interpersonal skills and using text communication. Factors that reduced its effectiveness were related to poor timeliness in response to their service requests, experiencing no change in their presenting problem, and not knowing what postcounseling action to take. Online counsellors need to be aware of these TBOC factors in order to best assess, educate, and respond to the needs of their clientele and provide them with the best therapeutic experience possible.

Conflicts of Interest

Pablo Navarro 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 no conflicts of interest.

Multimedia Appendix 1

Full pilot study survey.

[PDF File (Adobe PDF File), 70KB - mental_v6i7e13152_app1.pdf]

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Abbreviations

e-mental: electronic mental
SMS: short message service
TBOC: text-based online counseling

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Original Paper

Predicting Posttraumatic Stress Disorder Risk: A Machine Learning Approach

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Abstract

Background: A majority of adults in the United States are exposed to a potentially traumatic event but only a handful go on to develop impairing mental health conditions such as posttraumatic stress disorder (PTSD).

Objective: Identifying those at elevated risk shortly after trauma exposure is a clinical challenge. The aim of this study was to develop computational methods to more effectively identify at-risk patients and, thereby, support better early interventions.

Methods: We proposed machine learning (ML) induction of models to automatically predict elevated PTSD symptoms in patients 1 month after a trauma, using self-reported symptoms from data collected via smartphones.

Results: We show that an ensemble model accurately predicts elevated PTSD symptoms, with an area under the curve (AUC) of .85, using a bag of support vector machines, naive Bayes, logistic regression, and random forest algorithms. Furthermore, we show that only 7 self-reported items (features) are needed to obtain this AUC. Most importantly, we show that accurate predictions can be made 10 to 20 days posttrauma.

Conclusions: These results suggest that simple smartphone-based patient surveys, coupled with automated analysis using ML-trained models, can identify those at risk for developing elevated PTSD symptoms and thus target them for early intervention.

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KEYWORDS

PTSD; machine learning; predictive algorithms

Introduction

Background

Posttraumatic stress disorder (PTSD) is a psychiatric condition that leads to significant disability and impairment [1]. Early interventions administered shortly after a traumatic event can reduce the onset of PTSD and associated long-term impairment [2]. Given the costs associated with early intervention, it is not feasible or necessary to intervene with everyone exposed to these events—rather, a screen-and-treat approach is recommended in which those at high risk for PTSD are identified and treated. A key barrier to providing early intervention is an inability to accurately identify those at high risk for PTSD in this acute posttrauma period (<30 days following an event). The limited ability to detect those at risk stems from a limited understanding of how PTSD symptoms develop and, thus, what factors are most helpful in determining risk for the disorder.

A diagnosis of PTSD requires symptoms to be present for at least 30 days. Previous studies suggest that symptoms first appear in the days and weeks after a traumatic event and gradually increase over time [3,4]. Therefore, it may be possible to identify those at risk for PTSD by monitoring the progression of symptoms during this early period. Other previous studies have shown that effective monitoring and data collection can be implemented via smartphone surveys [5,6]. We hypothesized that predictive models based on statistical correlations between observable symptoms shortly after a traumatic event and eventual PTSD symptomology can be developed. Such predictive models would allow individuals at elevated risk for more severe psychopathology to be identified and provided with an early intervention.

In this paper, we take the initial steps toward such a predictive model. We investigated whether correlations exist between PTSD symptoms present shortly after trauma and at 1 month after an event and whether these correlations can be discovered by supervised *machine learning* (ML) approaches. Previous studies have shown that ML techniques are effective for predictive modeling in a medical setting, for example, to predict cancer prognoses [7]. However, such models have yet to be regularly implemented in psychiatric conditions. Furthermore, models induced by ML can be thoroughly vetted by techniques such as cross-validation, increasing confidence in their relevance.

The study presented here uses data collected during a clinical study involving 90 individuals who experienced a criterion A traumatic event and who were recruited from the critical care service of a level-1 trauma center in Northern New England [6]. PTSD symptoms were assessed using validated clinical scales. For this study, we prepared disjoint training, testing, and cross-validation datasets from the provided data for ML analysis. Our dataset is described in further detail in the Dataset section.

In this study, we took a comparative approach to investigating not only whether predictive ML-induced models may exist but also which are the best approaches to model the induction. The development of PTSD symptoms among those who go on to have severe PTSD symptoms follows a complex course, which may be nonlinear [3,8]. Hence, we considered nonlinear ML techniques, in particular, support vector machines (SVMs) with nonlinear kernels and random forest (RF). We also emphasized ensemble techniques that combine predictions from multiple models to obtain an improved prediction.

Specifically, this study considered 4 research hypotheses:

- Hypothesis 1: ML can demonstrate significant statistical correlations between observable symptoms and elevated PTSD 1 month after trauma.
- Hypothesis 2: ML can identify the relevance of early symptoms used to predict PTSD by care providers.
- Hypothesis 3: ML can identify the number of days needed to predict elevated PTSD 1 month after trauma.
- Hypothesis 4: ML-induced models can be used to predict elevated PTSD 1 month after a trauma, given that symptoms are displayed between 10 and 20 days posttrauma.

Dataset

In this section, we describe the dataset we used for our study, which was collected during a clinical study involving 90 individuals who experienced a criterion A traumatic event and were recruited from the critical care service of a level-1 trauma center in Northern New England [6]. We also describe our data preprocessing methods and feature correlation and feature importance analyses on the preprocessed data.

Data Collection

To recruit participants in the cited study [6], a trained research assistant approached the prospective participants at the bedside in the hospital and administered an initial assessment battery to determine if the trauma they experienced met the criterion A for a diagnosis of PTSD. Participants were met bedside by a care provider within a mean of 4.88 days and an SD of 5.22 days after their traumatic event. Participants then downloaded a mobile app to their device that administered the assessment surveys. The app used for this study was Metricwire [9], a platform that allows the administration of self-reported surveys on a mobile device over a predefined period. Metricwire was available for download for free from the respective app stores.

Participants (N=90) were aged mean 35 (SD 10.41) years, were a majority of males (n=57), and had completed college (n=36). The sample was predominately white (n=80). The most common type of injury was motor vehicle accident (n=45). Cell phone ownership included 52 iPhones and 35 Android devices. In addition, 3 participants identified having another type of device but had access to an Android or iPhone device. PTSD symptoms were assessed with the PTSD checklist-5 at 1-month posttrauma [10]. According to the Diagnostic and Statistics Manual 5th Edition (DSM-5) criteria, the PTSD checklist for DSM-5 (PCL-5) is a 20-item self-reported measure that assesses PTSD symptoms experienced over the last month. Items assess symptoms across 4 symptom clusters of PTSD (re-experiencing, negative mood, avoidance, and hyperarousal) on a 0- to 4-point Likert scale. Total scores range from 0 to 80. A score of 33 or higher is associated with a likely diagnosis of PTSD [11].

Each mobile assessment consisted of 10 items. These included the 8 items (items 1, 4, 6, 7, 9, 12, and 18) of the abbreviated PCL-5 [8] and an additional item from the PCL-5 assessing sleep (PCL-5 item 20). The abbreviated PCL was used to minimize the burden to participants in that they had to complete 10 items as opposed to 21. The tenth item assessed pain on a scale of 0 to 10. Preliminary testing suggested it took approximately 5 min to complete each assessment. Each day for 30 days following initial assessment, the participants received a local notification on their mobile device to complete a survey. Participants had 10 hours to complete a survey regarding the symptoms for that day and were allowed to skip questions. Responses were uploaded immediately upon completion of each survey. After 30 days, participants received a notification that they no longer had to complete assessments but could continue to use the system for an additional 60 days at their discretion. Participants were compensated US $1 for each assessment completed within the first 30 days. The overall response rate for the combined sample was 78.0% (mean 23.33, SD 16.36 assessments). A majority of the sample (46/90, 51.1%) completed 75.0% or more of the assessments, resulting in 4312 assessments distributed over different days of the study. The rate of responding was compared with the mean rates reported in previous studies (mean 65.34%) [5,12,13]. Our study aimed to determine if elevated symptoms could be predicted solely based on these data collected via mobile phones as other input variables may not be available in certain clinical settings.

Data Selection

Data, in the form of 11 main features, were collected from each patient, namely, *Days.since.trauma*, $Reexp_1$, $Reexp_2$, $Avoid_1$, $Avoid_2$, $NACM_1$, $NACM_2$, AAR_1, AAR_2, *Sleep*, and *Pain*, shown and described in Table 1. To build the labels, a target variable was created for each row, $Target_{33}$, based on the following conditions:

$Target_{33}=1$, when $PTSD.Severity \geq 33$.

$Target_{33}=0$, otherwise.

The experiments were conducted using a score of 33, which corresponds to a clinical cutoff for likely PTSD [11]. These cutoffs allow for the research to be conducted as a classification problem with a target value of either 0 or 1.

Although the features shown in Table 1 have been recommended by medical experts, in this study, we determined the feature relevance based on a given feature's ability to predict PTSD within the context of ML algorithms. The role of feature selection in this context is to ultimately reduce the number of symptoms that need to be assessed for accurate prediction. Proper feature selection should reduce overfitting and, therefore, increase accuracy as well as reduce model training and inference time [14].

Data Preprocessing

After determining the relevant features and target binary classification labels (PTSD or no PTSD at threshold value 33), the resulting data still contained a nontrivial amount of missing data. Specific patient response instances with missing values were not removed as they could potentially retain relevant information. Instead, missing values were replaced with an average calculated from the associated patient's previous entries. Figure 1 shows the missing value distribution for each feature.

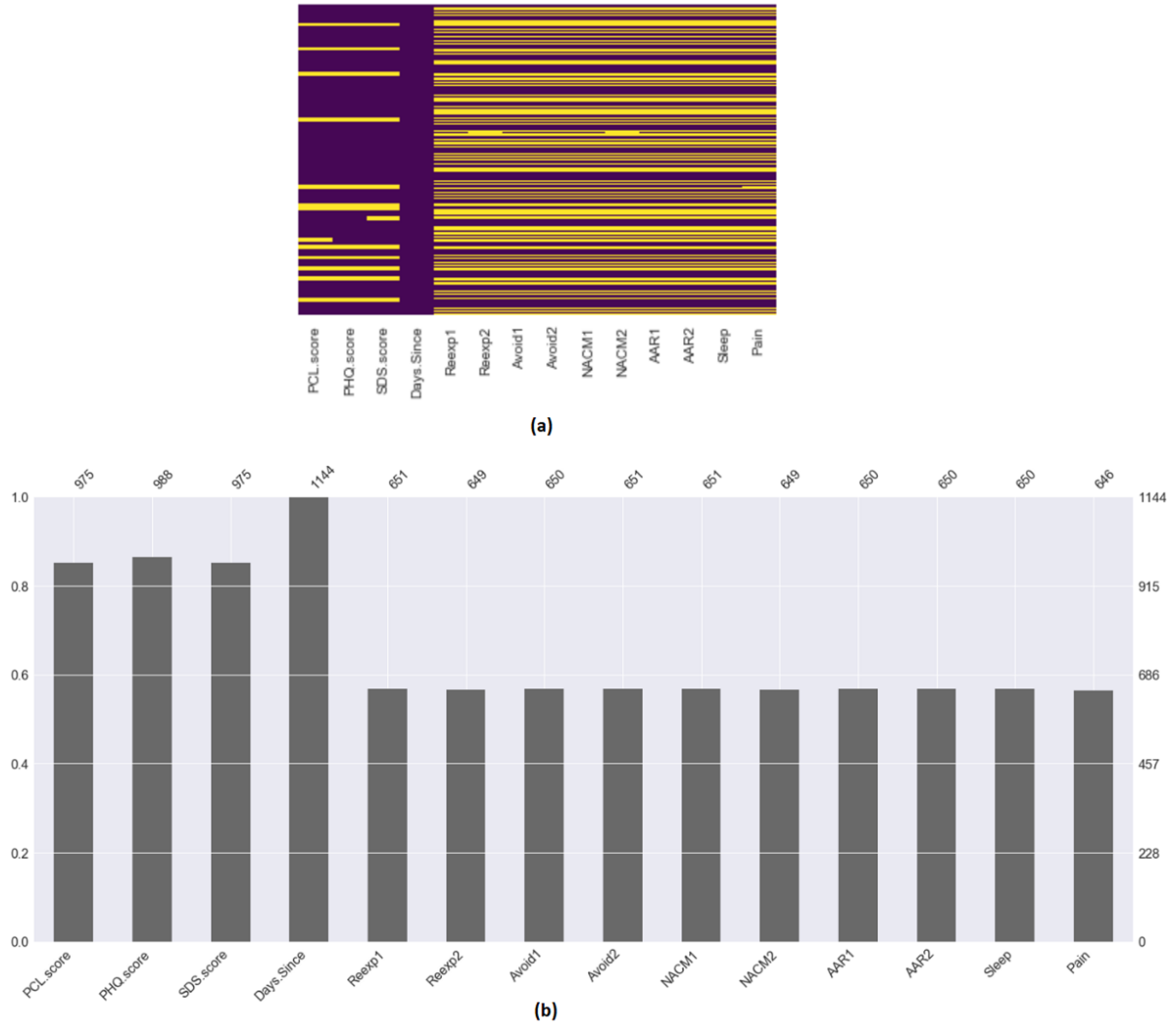
Standardization or normalization of features is a common preprocessing step in ML, producing features centered around a zero mean with unit variance. Feature standardization is a requirement for gradient descent–based ML algorithms (such as SVMs and logistic regression) for faster convergence and better performance. The general method for calculating standardized features is:

where for a given feature x is the original value, is the normalized value, is the mean value, and σ is the SD.

Table 1. Dataset table (higher values signify more severe pathology).

Attribute (feature)	Description	Nonnull value	Range
PTSD.Severity (1 month)	Posttraumatic stress disorder symptoms 1-month posttrauma	975	0-80
Days.since.trauma	Days since trauma occurred	1144	1-49
$Reexp_1$	Distress related to trauma-related intrusive thoughts	651	0-4
$Reexp_2$	Emotional reactivity to trauma cues	649	0-4
$Avoid_1$	Avoidance of thoughts about trauma	650	0-4
$Avoid_2$	Avoidance of environmental trauma-related reminders	651	0-4
$NACM_1$	Negative beliefs about self and the world	651	0-4
$NACM_2$	Loss of interest in activities	649	0-4
AAR_1	Exaggerated startle reaction	650	0-4
AAR_2	Difficulty in concentrating	650	0-4
Sleep	Sleep difficulty	650	0-4
Pain	Self-reported pain	646	0-10

Figure 1. (a) Missing feature value distribution across all data input vectors. Yellow signifies missing values. (b) Missing feature percentage. *PTSD.Severity*: posttraumatic stress disorder symptoms. *Days.since.trauma*: days since trauma occurred. $Reexp_1$: distress related to trauma-related intrusive thoughts; $Reexp_2$: emotional reactivity to trauma cues; $Avoid_1$: avoidance of thoughts about trauma; $Avoid_2$: avoidance of environmental trauma-related reminders; $NACM_1$: negative beliefs about self and the world; $NACM_2$: loss of interest in activities; AAR_1: exaggerated startle reaction; AAR_2: difficulty in concentrating; *Sleep*: sleep difficulty; *Pain*: self-reported pain.

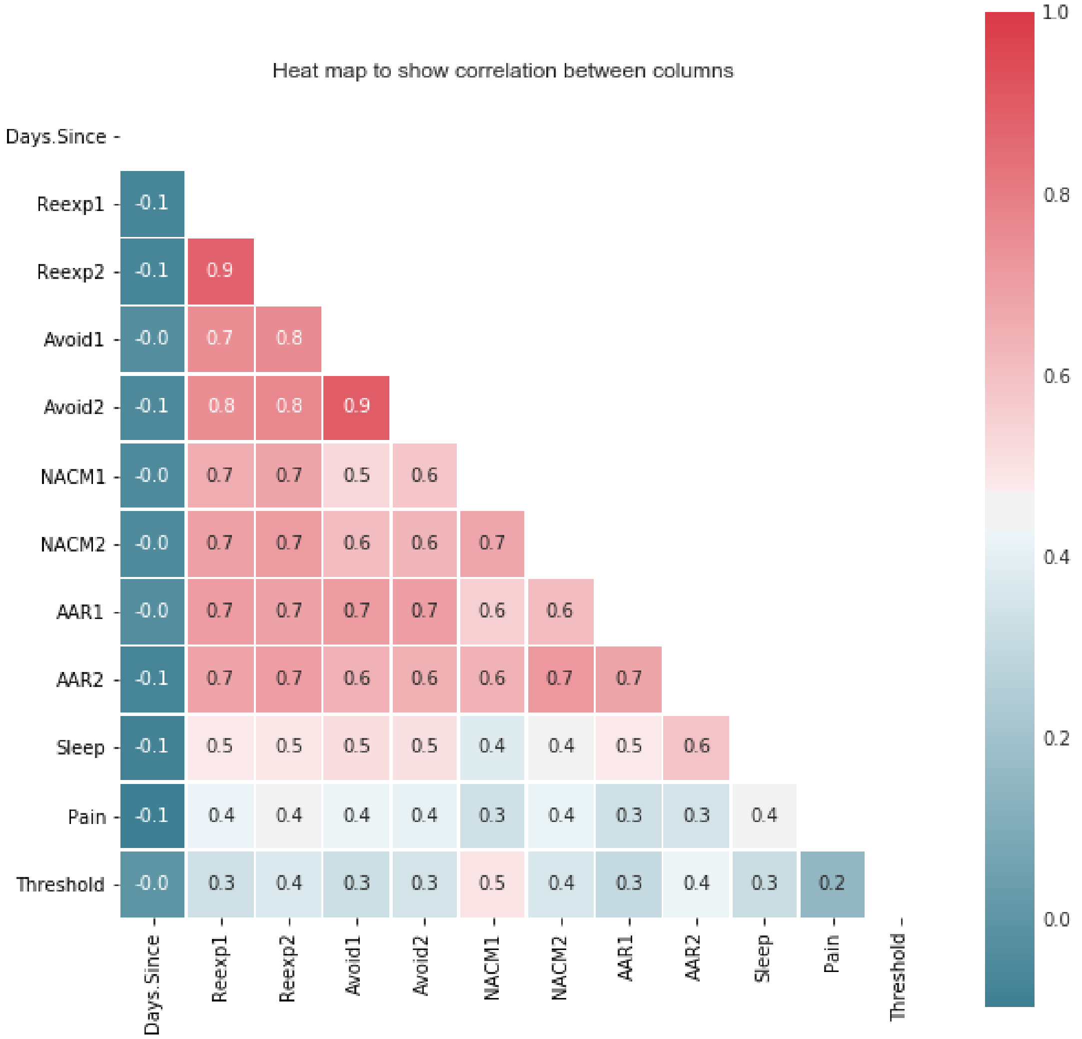


Feature Correlation

To identify both feature relevance and potential duplication of information surrounding early symptoms used to predict PTSD, we measured the correlation between all pairs of features. The correlation is statistically calculated between each feature variable and another using the average of the products between the standardized values of each sample. This process summarizes the relationship between features, known in statistics as the covariance method.

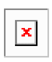
In general, removing correlated features will not always enhance model performance but can aid in data preparation for ML algorithms. More importantly, this process can reduce the number of symptoms needed to predict PTSD. Figure 2 shows the correlation between features in our dataset. The aim of this correlation study was to reduce features in the event that 2 features are highly correlated. In particular, we noticed that $Reexp_1$, $Reexp_2$, $Avoid_1$, and $Avoid_2$ were highly correlated. Thus, $Reexp_2$ was retained, whereas $Reexp_1$, $Avoid_1$, and $Avoid_2$ were removed from our input feature set. Later, in the Results section, we discuss in detail the effect of this feature selection on model performance.

Figure 2. Correlation between features in our dataset, prior to feature selection. *PTSD.Severity*: posttraumatic stress disorder symptoms. *Days.since.trauma*: days since trauma occurred. $Reexp_1$: distress related to trauma-related intrusive thoughts; $Reexp_2$: emotional reactivity to trauma cues; $Avoid_1$: avoidance of thoughts about trauma; $Avoid_2$: avoidance of environmental trauma-related reminders; $NACM_1$: negative beliefs about self and the world; $NACM_2$: loss of interest in activities; AAR_1: exaggerated startle reaction; AAR_2: difficulty in concentrating; *Sleep*: sleep difficulty; *Pain*: self-reported pain.



Feature Importance

Feature importance methods score each feature by providing a quantitative measurement surrounding its relevance. The RF algorithm is capable of providing an importance score for each feature. RF can score the relevance of each feature through either statistical permutation tests or the Gini impurity index, which is used in this study, as shown in Figure 3. In the RF, a Gini impurity index is calculated at each node split using 1 feature variable to measure the quality of the split across classes at the considered node. The Gini impurity index is computed via the following equation:



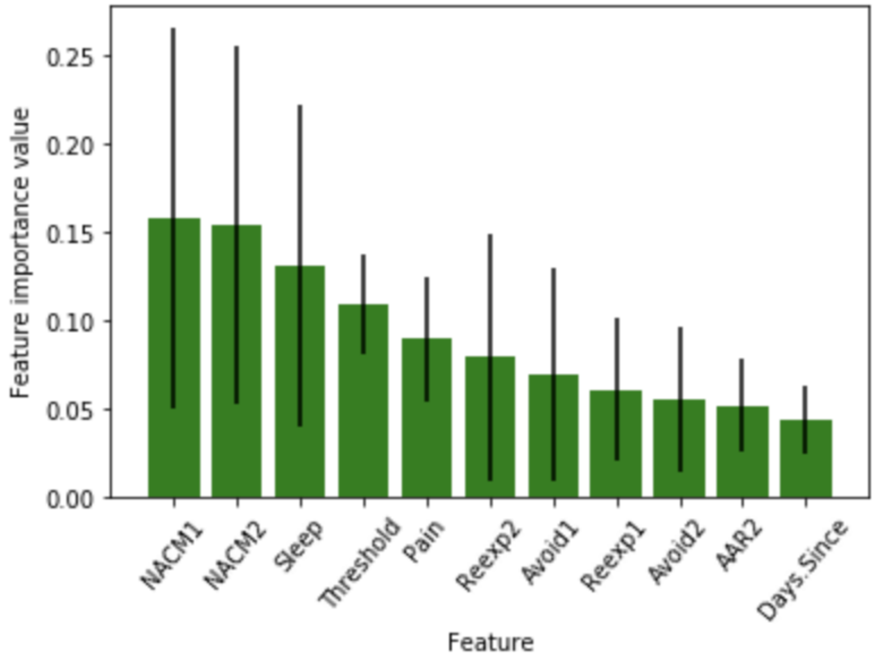
where *c* is the number of classes in the feature and p_i is the fraction of samples labeled with class *i*.

To calculate feature importance, we sum the Gini impurity index values for each feature in the dataset over RF trees. These sums are then normalized and ranked to indicate the feature importance index. For more details on the Gini variable importance approach, see the study by Garcia-Lorenzo et al [15].

Features with smaller importance values can be removed from the dataset, thus, further reducing the number of relevant early symptoms to be used for PTSD prediction. Figure 3 shows that AAR_2, $Avoid_2$, and $Reexp_1$ are less important than others. Furthermore, although the *Days.since.trauma* feature has a low score, this is an expected result, and this feature is, therefore, retained to provide important temporal information to the model.

In the Results section of this study, we discuss the effect of removing AAR_2, $Avoid_2$, and $Reexp_1$ as they are low in importance, as well as $Reexp_1$, $Avoid_1$, and $Avoid_2$, which are highly correlated with $Reexp_2$, as discussed above. Notice that $Reexp_1$ and $Avoid_2$ are both low in importance and highly correlated with other features.

Figure 3. Ranked feature importance determined using the Gini method. *PTSD.Severity*: posttraumatic stress disorder symptoms. *Days.since.trauma*: days since trauma occurred. *Reexp*$_1$: distress related to trauma-related intrusive thoughts; *Reexp*$_2$: emotional reactivity to trauma cues; *Avoid*$_1$: avoidance of thoughts about trauma; *Avoid*$_2$: avoidance of environmental trauma-related reminders; *NACM*$_1$: negative beliefs about self and the world; *NACM*$_2$: loss of interest in activities; *AAR*$_1$: exaggerated startle reaction; *AAR*$_2$: difficulty in concentrating; *Sleep*: sleep difficulty; *Pain*: self-reported pain.



Methods

In this paper, we studied multiple classifiers—logistic regression, naive Bayes, SVM, and RFs—to classify PTSD versus non-PTSD cases. In addition, we proposed *ensembles* of all these classifiers. It is known that ensembles of classifiers can form a better classifier than individual classifiers [16]. Ensemble methods combine predictions from several classifiers, or from a single classifier with different hyperparameters, to ultimately improve robustness as compared with a single estimator.

Machine Learning Algorithms

Multiple binary classifiers were chosen for use in this study because of their established predictive power.

Logistic Regression

We applied logistic regression because it is widely used for binary classification problems. We built a linear classifier without performing any nonlinear transformation on the features. For more information about logistic regression classifiers, refer to the study by Held [17].

Naive Bayes

The naive Bayes classifier is simple, fast, and reliable and is derived from the Bayes theorem. The naive Bayes classifier assumes independent features with conditional independence, making the computation simpler (hence, *naive*). For more information about naive Bayes, refer to the study by Chan [18].

Support Vector Machines

SVMs are known for their generalization power, where the SVM kernel trick is used to implicitly enforce a nonlinear transformation on input features. In this study, we used linear, Gaussian Radial basis function (RBF), and polynomial kernels. We expect the results of the linear SVM to have similar or close results to the logistic regression classifier. For more information about the SVM algorithm, refer to the study by Burges [19].

Random Forests

RFs are an ensemble learning approach made up of multiple small decision trees, which are trained on a subset of data and features at each node split. In this study, we used RFs because of their predictive power and ability to work despite missing data (in light of missing data in our dataset). We did *not* replace missing data with associated average values for training RFs and, instead, we changed the relevant entries to be -1. For more information about RFs, refer to the study by Breiman [20].

Ensemble Methods

Ensemble methods work by combining several weaker classifier predictions, thus improving overall robustness. In this study, we ensembled the single classifiers: SVM (linear, Gaussian, and polynomial kernels), logistic regression, naive Bayes, and RF algorithms. We investigated 2 main techniques.

Hard Voting (Majority Voting)

In the case of hard voting, the final predicted class is taken to be the majority class label, as predicted by each individual classifier.

Weighted Average Probabilities (Soft Voting)

In the case of soft voting, the class label is calculated by summing the predicted probabilities across each class label and classifier and subsequently selecting the class with the highest probability. For this ensemble method, we used a uniform weight distribution.

Prediction Performance Versus Days Posttrauma

To study the effect of time posttrauma on prediction performance, we trained the proposed classifiers on several different cutoff days. Specifically, we evaluated our models on data over 7, 10, 15, 20, 25, 30, 35, and all days posttrauma. Through comparative analysis, our aim was to determine how long surveys need to be performed to accurately predict elevated PTSD symptoms 1-month posttrauma.

Reducing Features

We also studied the effect of reducing the number of indicators (features) based on the feature correlation and feature importance methods discussed above. On the basis of these, we modeled without the features AAR2, Reexp1, Avoid1, and Avoid2, as they are highly correlated with other features or low in importance.

Evaluation

Standard scoring metrics for ML models include accuracy (or error rate), true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), false negative rate (FNR), recall-precision curves, and receiver operating characteristics (ROC) curves. These metrics provide a simple and effective way to measure the performance of a classifier [21]. In our evaluation, we focus on accuracy, confusion matrices, and ROC curves.

These scoring methods have been evaluated using 2 main methods: the holdout method [22] and the cross-validation method [23].

Holdout Method

For the implementation of the ML algorithms, our dataset was partitioned randomly into 70.0% and 30.0% for training and testing, respectively. The training set is used to train the models and to find the model hyperparameters, whereas the testing set is used to evaluate the model performance and its ability to generalize to new unseen data. The hyperparameters used for all the classifiers were manually assigned, and then hyperparameter tuning was performed using random search, as described in the study by Bergstra and Bengio [24].

Accuracy

Accuracy is a common metric to evaluate the performance of ML algorithms. It gives the ratio of correct predictions over the total number of predictions. In the case of imbalanced datasets, classification accuracy alone is insufficient to determine if the model is robust. For example, in a notable degenerative case, a model can predict only the majority class label and still achieve high classification accuracy.

K-Fold Cross-Validation

Models trained using a holdout technique might overfit or underfit depending on the distribution of the data split. To overcome this issue, K-fold cross-validation was performed on the dataset. This technique divides data into equal disjoint subsets of size K. The model being evaluated is then trained on all folds except one, which is reserved for testing. This process is then repeated K−1 times, selecting each fold to be used for testing one time. Finally, the results from each of the testing folds are averaged and returned as the final results. In this study, we used 10 folds, each fold is used once in testing and 9 times in training. This 10-fold cross-validation reduces the variance in the results by averaging over 10 different partitions, providing more reliable and generally accurate methodology than the Holdout method.

Confusion Matrix

Confusion matrices offer a comprehensive evaluation of the quality of an ML algorithm. In contrast to the singular dependence on 1 number from the accuracy metric, a confusion matrix provides a method of evaluating performance across all of the classes. For binary classification, the confusion matrix is simplified to 2 classes as follows:

$$[\ TP\ FP\ FN\ TN]$$

where, TP is the number of true positives, FP is the number of false positives, FN is the number of false negatives, and TN is the number of true negatives. TP and TN represent the number of correctly predicted labels, whereas FP and FN are those that are mislabeled by the classifier. The higher true values in the confusion matrix the better, indicating more correct predictions.

Receiver Operating Characteristics Curve

The ROC curve is a simple graphical representation and powerful methodology to evaluate binary classifiers. It has become a popular method because of its ability to evaluate overall performance [25].

The ROC space is built and plotted using TPR and FPR from the equation TPR and FPR as the y-axis and x-axis, respectively. Each point (FPR, TPR) represents a classifier at a different threshold applied to the predicted labels' probability [26] as shown by the following equations:

Independent of class distribution and error costs, the ROC curve connects the points in the ROC space. ROC curves describe the predictive performance and characteristics of a classifier at different probability levels. The area under the ROC curve, denoted as area under the curve (AUC), can be used to rank or compare the performance of classifiers [25]. AUC has been proven to be more powerful than accuracy in experimental comparisons of several popular learning algorithms [27], and in fact, we treat this as our *gold standard* evaluation method.

Results

Machine Learning Algorithms

For RFs, we used the Gini [28] algorithm to measure the quality of a split and 11 estimators. For logistic regression and SVMs, hyperparameter tuning was performed based on the random search technique described in the study by Bergstra and Bengio [24]. Results obtained after 50 random searches were as follows:

- Logistic regression, Lambda=0.02380
- SVM-linear kernel, C=62
- SVM-RBF kernel, C=57, Sigma =0.004
- SVM-polynomial kernel C=44, Sigma =0.017, degree=3

Where C and Lambda are the regularization terms and Sigma is the Gaussian kernel parameter. For ensemble methods, we investigated 2 main techniques: hard voting (majority voting) and weighted average probabilities (soft voting). For soft voting, we equally weighted the predicted probabilities from each classifier. We ensembled all the classifiers, that is, logistic regression, naive Bayes, SVM with linear kernel, SVM with Gaussian kernel, SVM-polynomial kernel, and RF.

Accuracy

Table 2 shows the accuracy of various models in both the train-test split (holdout) and cross-validation methods. As shown in the table, the cross-validation can deal with the drawbacks of train-test split (holdout) technique, and therefore, it is a more reliable and generalized accuracy method than the holdout method. Thus, for the rest of our experiments, we exclusively used cross-validation.

Receiver Operating Characteristics Curves

Figure 4 and Table 3 show the ROC curves for singular and ensemble models and the AUC.

Reduced Features Analysis

We reduced the use of AAR_2, $Reexp_1$, $Avoid_1$, and $Avoid_2$ features because of their high correlation and low predictive power, as discussed in the Feature Correlation and Feature Importance dataset subsections. Figure 5 and Table 4 show the ROC curve and the AUC for singular and ensemble models, respectively, with those features eliminated.

Table 2. Accuracy results.

Machine learning method	Train-test accuracy	Cross-validation accuracy
Logistic regression	.8735236	.82110961
Naive Bayes	.8711414	.82210961
SVM[a]-linear kernel	.8349277	.76406263
SVM-Gaussian kernel	.8632561	.81908724
SVM-polynomial kernel	.8682245	.81857010
Random forest	.8212457	.77888143
Voting classifier-soft	.8798578	.82045190
Voting classifier-hard	.85919181	.80702013

[a]SVM: support vector machine.

Figure 4. Receiver operating characteristics graphs for single and ensemble models. SVM: support vector machine; RBF: Radial basis function.

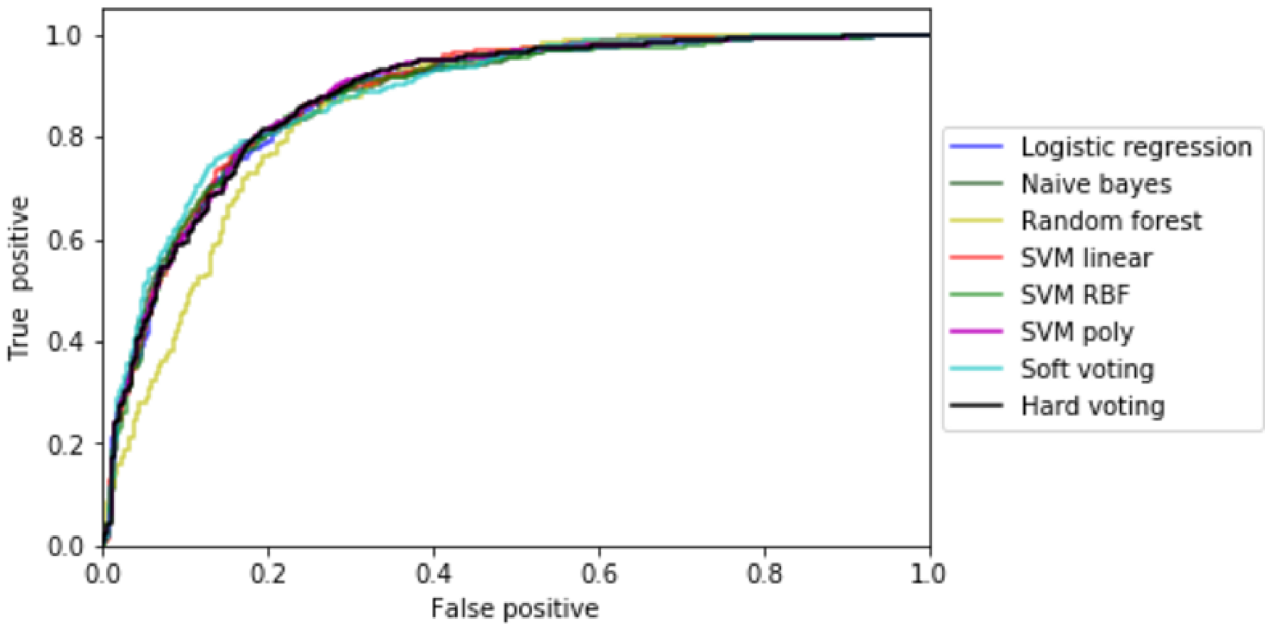


Table 3. Area under the curve results.

Machine learning model	Receiver operating characteristics area under the curve
Logistic regression	.8325350
Naive Bayes	.8422145
SVM[a]-linear kernel	.8179543
SVM-Gaussian kernel	.8465576
SVM-polynomial kernel	.8337800
Random forest	.7844874
Voting classifier-soft	.8559346
Voting classifier-hard	.8357976

[a]SVM: support vector machine.

Figure 5. Receiver operating characteristics graphs for single and ensemble models with difficulty in concentrating, distress related to trauma-related intrusive thoughts, avoidance of thoughts about trauma, and avoidance of environmental trauma-related reminders features eliminated. SVM: support vector machine; RBF: Radial basis function.

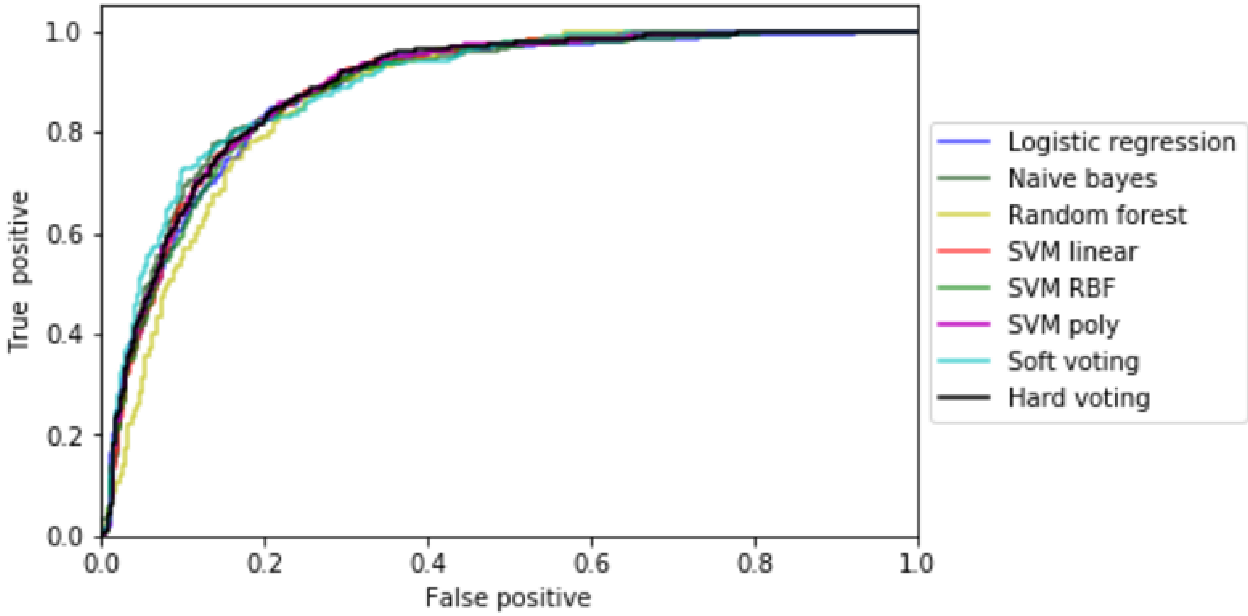


Table 4. Receiver operating characteristics area under the curve for reduced features models.

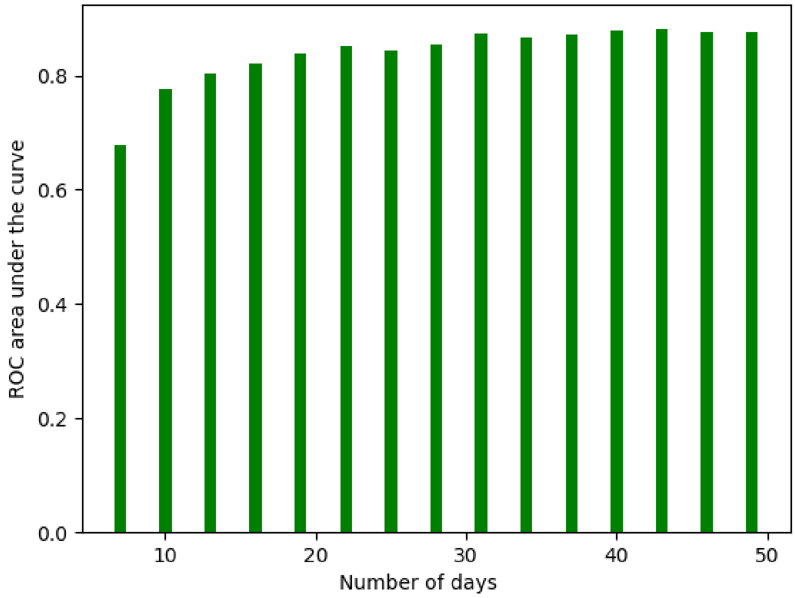
Machine learning model	Receiver operating characteristics area under the curve
Logistic regression	.87685409
Naive Bayes	.88154251
SVM[a]-linear kernel	.87553263
SVM-Radial basis function kernel	.88182758
SVM-polynomial kernel	.88158036
Random forest	.85092592
Voting classifier-soft	.88920514
Voting classifier-hard	.88145900

[a]SVM: support vector machine.

Prediction Performance Versus Days Posttrauma

Figure 6 shows the AUC of ROC curves for the ensemble model trained using the reduced features settings from the first 7, 10, 15, 20, 25, 30, and 35 days or all 45 days of patient data. These results demonstrate that an ensemble model has the same predictive power with 30 days of symptom reporting as it does with 45.

Figure 6. Area under the curve for the system trained and evaluated on different numbers of days. ROC: receiver operating characteristics.



Discussion

Principal Findings

As discussed in the Results section, Figure 4 and Table 3 show that the SVM with a Gaussian kernel outperformed other single classifiers. SVMs usually generalize better than other ML algorithms as they maximize the margin between classes. It is also interesting to see that RFs performed comparatively poorly as it is a very powerful classifier and usually works well in case of missing data. Ensemble methods showed slightly better performance than single classifiers.

In addition, as shown in Figure 5 and Table 4, our results show significant performance enhancement by reducing features, indicating a high-variance system and suggesting that simplifying self-reporting questionnaires may yield better results. Reducing more features beyond AAR_2, $Reexp_1$, $Avoid_1$, and $Avoid_2$ did not improve the performance, indicating that these features might be considered noise and could be eliminated from the study. This reduction eliminated symptoms from the avoidance cluster of PTSD. Although these results suggest that the removal of these symptoms did not impact prediction, replication is needed before firm conclusions can be made about the role these symptoms play in PTSD prediction. Allowing for a shorter survey by removing these items reduces the burden of each assessment and is likely to increase survey compliance, which will provide a more accurate assessment of recovery.

Finally, as a key result, Figure 6 shows that the ensemble model can be used to predict elevated PTSD 1 month after a trauma, given that symptoms are displayed between 10 and 20 days posttrauma, with only a (5.0/100)% drop in performance. Each experiment in Figure 6 has been conducted independently. Thus, patients who are correctly classified using data from fewer days have no guarantee to be correctly classified by giving data from more days, even though it is very likely.

In summary, our results shed light on our research hypotheses stated in the Introduction section, as follows.

Results for Hypothesis 1

An ML-induced ensemble model is able to demonstrate significant statistical correlations between observable symptoms and elevated PTSD 1 month after trauma with an AUC of 0.85, as shown in Table 3 and Figure 4. In addition, we have demonstrated that an SVM with Gaussian kernel outperformed other single ML algorithms.

Results for Hypothesis 2

As detailed in the Results section, under the *Reduced Features Analysis* subsection, we have demonstrated that a subset of 7 standard early symptoms used to predict PTSD by care providers is adequate to predict elevated PTSD 1 month after a trauma.

Results for Hypothesis 3

In the Results section, under the *Prediction Performance Versus Days After Posttrauma* subsection, we showed that an ensemble model has the same predictive power between 30 days and the full 45 days of the study period.

Results for Hypothesis 4

In the Results section, under the *Prediction Performance Versus Days After Posttrauma* subsection, we showed how an ensemble model can be used to predict elevated PTSD 1 month after a trauma, given that symptoms are displayed between 10 and 20 days posttrauma, with only a (5.0/100)% drop in performance, as compared with a prediction at 30 days.

Conclusions

Our experimental results are quite promising in that they suggest the potential for using a combination of self-reported symptoms and ML-induced models to automatically predict elevated PTSD in a manner that supports earlier interventions by care providers for 10 to 20 days posttrauma. These results were obtained using only data collected with a mobile device, suggesting that this method of symptom tracking is widely disseminable. Furthermore, our results suggest that smartphone surveys for self-reporting symptoms can be simplified more than previously understood.

We also explored various techniques for building predictive models. Although nonlinear learners did not outperform linear learners, an ensemble method with nonlinear models performed marginally better than single-linear models and will form the basis of our ongoing work in this area. In future studies, we plan to explore the application of these tools in a real clinical setting as a means to provide better care for at-risk patients. The prediction algorithm might also be improved if additional data were incorporated, such as baseline PTSD symptoms, demographic variables, and trauma histories, which is also an interesting topic for future studies.

Conflicts of Interest

None declared.

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Abbreviations

AUC: area under the curve
FPR: false positive rate
ML: machine learning
PTSD: posttraumatic stress disorder
RBF: Radial basis function
RF: random forest
ROC: receiver operating characteristics
SVM: support vector machine
TPR: true positive rate

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Original Paper

Digital Games and Mindfulness Apps: Comparison of Effects on Post Work Recovery

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Abstract

Background: Engagement in activities that promote the dissipation of work stress is essential for post work recovery and consequently for well-being. Previous research suggests that activities that are immersive, active, and engaging are especially effective at promoting recovery. Therefore, digital games may be able to promote recovery, but little is known about how they compare with other popular mobile activities, such as mindfulness apps that are specifically designed to support well-being.

Objective: The aim of this study was to investigate and compare the effectiveness of a digital game and mindfulness app in promoting post work recovery, first in a laboratory setting and then in a field study.

Methods: Study 1 was a laboratory experiment (n=45) in which participants' need for recovery was induced by a work task, before undertaking 1 of 3 interventions: a digital game (*Block! Hexa Puzzle*), a mindfulness app (*Headspace*), or a nonmedia control with a fidget spinner (a physical toy). Recovery in the form of how energized participants felt (energetic arousal) was compared before and after the intervention and how recovered participants felt (recovery experience) was compared across the conditions. Study 2 was a field study with working professionals (n=20), for which participants either played the digital game or used the mindfulness app once they arrived home after work for a period of 5 working days. Measures of energetic arousal were taken before and after the intervention, and the recovery experience was measured after the intervention along with measures of enjoyment and job strain.

Results: A 3×2 mixed analysis of variance identified that, in study 1, the digital game condition increased energetic arousal (indicative of improved recovery) whereas the other 2 conditions decreased energetic arousal ($F_{2,42}$=3.76; P=.03). However, there were no differences between the conditions in recovery experience ($F_{2,42}$=.01; P=.99). In study 2, multilevel model comparisons identified that neither the intervention nor day of the week had a significant main effect on how energized participants felt. However, for those in the digital game condition, daily recovery experience increased during the course of the study, whereas for those in the mindfulness condition, it decreased ($F_{1,18}$=9.97; P=.01). Follow-up interviews with participants identified 3 core themes: *detachment and restoration*, *fluctuations and differences*, and *routine and scheduling*.

Conclusions: This study suggests that digital games may be effective in promoting post work recovery in laboratory contexts (study 1) and in the real world, although the effect in this case may be cumulative rather than instant (study 2).

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KEYWORDS

play; occupational health; mindfulness

Introduction

Background

Workplaces demands on an individual's physical, psychological, and emotional resources [1]. The need for rest and recovery exists across all employment environments, working patterns, and industries. Without sufficient recovery, negative strain and workload weigh on resources and can result in poor well-being, which can pose significant health risks over time [2,3]. Therefore, post work recovery (ie, the process of replenishing depleted resources after a day of work [2-4]) is vital in avoiding the physical and psychological health complaints associated with accumulated work stress [1,5]. In addition, successful recovery has been shown to have positive effects, for example, in encouraging positive affect [6,7] and encouraging greater work engagement, proactive behavior, and the pursuit of learning goals [8].

For recovery to be successful, 4 aspects need to be satisfied. These are psychological detachment (spending time not thinking about work), relaxation, mastery (the sense of gaining skills in something other than work), and control (the experience of having control within or over activities) [4]. Although the type of job itself plays an important part in recovery and work-related stress, leisure time is increasingly being appreciated as instrumental in this process [9]. Evidence suggests that mentally engaging leisure activities, for instance, are more effective than more passive activities [4]. Relaxing and socially oriented pastimes have been found to reduce work demands and negative affect during breaks [10], and activities such as sport or exercise have been highlighted as especially useful in improving recovery [11].

However, for many, leisure time recovery is difficult to achieve; the present-day workforce is working longer hours [12], traveling further to work [13], and reporting increased work stress compared with those of the past, all of which negatively impact this process. Consequently, some of the most effective activities, for example, team sports [11], are difficult to incorporate into our already busy days. One pursuit that is already well integrated into our home lives is the use of electronic devices. Therefore, although there are several factors that can impact the recovery experience itself, here we consider the role that digital technology can play in supporting it. We focus on the potential benefits of playing digital games and engaging with mindfulness apps and the role that the subjective experience of engaging in these activities might have. To this end, below, we outline the relevant literature regarding how these activities might impact recovery. Then, we describe 2 studies: Study 1 tests whether a digital game, mindfulness app, or no-activity control condition improves recovery after a work task in a laboratory setting. Study 2 takes an in-the-wild approach, aiming to more closely replicate how digital games and mindfulness apps might be used in real-world contexts. Study 2 therefore surveys workers over 5 days during which they either played a digital game or engaged with a mindfulness app after returning from work.

Related Studies

Understanding whether digital activities can be used to contribute to the process of recovery not only indicates whether low effort, easily accessible activities can be used for this purpose but also whether the wide range of people currently using devices in their spare time stand to benefit. Evidence suggests that not all media use is equal in terms of recovery outcomes. For example, research has shown that watching movie clips is more effective than a no-activity condition in terms of recovery experiences [14], with positively valenced movie clips also improving relaxation [15]. The degree of interactivity of the media also appears to be influential. Digital games have been argued to satisfy all 4 aspects of recovery: high interactivity and immersion allow for psychological detachment, games tend to be relaxing, players can control progress within games, and games provide opportunities for mastery and accomplishments [16]. Surveys have indicated that those who play games for recovery purposes are more likely to play them after a stressful work situation, with people experiencing higher levels of work fatigue playing more games [16]. Similarly, in workplace contexts, game use during work time has been associated with greater reported recovery from work-related fatigue [17]. Those who regularly play digital games have also been found to have a lower need for recovery than those who do not [18], with particularly strong associations between gameplay and both relaxation and psychological detachment.

However, there have been few attempts to confirm that this relationship is causal. In 1 laboratory study, Reinecke et al [19] found that following a work task, playing a digital game improved recovery to a greater degree than watching a noninteractive movie clip or a no-activity control. This provides some promising initial evidence for a causal role of digital games in post work recovery, but further replications are required, particularly in more naturalistic settings.

There are also other smartphone apps that remain relatively unexplored in terms of recovery, such as those for mindfulness. Despite the rise in interest in mindfulness practices [20], the proliferation of mindfulness apps [21,22] and the promises many of these apps make in terms of well-being–related outcomes [22], little research has focused specifically on recovery. However, there are indications that it might be beneficial in this area. For example, mindfulness involves a state of attention and awareness of both external and internal states and experiences without any attributed judgment or value, promoting a sense of being in the moment [23]. It is this nonjudgmental experiential processing that has been argued to be effective against negative thought patterns such as rumination or anxiety, resulting in positive psychological effects and overall well-being [24], although the extent to which this extends beyond a placebo effect has been questioned [25].

Being equipped with the skills to prevent the negative effects of overthinking or ruminating on negative events has clear applications to occupational contexts, and mindfulness practice has been argued to be related to a number of factors relevant to post work recovery, including greater work engagement [26], improved sleep quality [27-29], and reduced emotional exhaustion [30]. In terms of recovery, more specifically, relaxation is one of the primary goals of mindfulness practice, and an in-the-wild study on work-life balance found that recovery in terms of psychological detachment improved with the implementation of mindfulness activities [31]. However, positive results have not been universal; in a field experiment, despite finding that mindfulness training improved sleep quality, there was no effect on psychological detachment [27]. Mastery and control have not been directly explored in relation to mindfulness, but it is plausible, for instance, that the reflective attention and awareness involved in mindfulness might provide a sense of control over one's feelings or experiences and that improving one's ability to practice mindfulness might provide a sense of mastery. However, whether this is indeed the case is unclear.

There has also been little research into how mindfulness practice in the format of an app specifically affects recovery. However, mindfulness apps have been associated with increases in positive affect, particularly when the task was enjoyed [32], and Web-based delivery of mindfulness programs has performed as well as in-person equivalents in improving stress, sleep quality, and heart rate [29]. Therefore, although existing evidence suggests mindfulness apps have positive effects that might translate into recovery outcomes, this is yet to be confirmed, particularly in comparison with interactive media such as digital games.

Another important factor to consider is the subjective experience of the activity; an activity 1 person might think of as a chore might be considered a respite by others, for example, cooking [33]. Similarly, an individual might appraise the same activity as either restorative or laborious depending on the context. The distinction between enjoyable and unenjoyable activities can be highly influential in the subsequent recovery outcomes, with those that are more pleasurable being more restorative [3,10]. This pattern has also been observed in research focusing specifically on media use. For example, negative perceptions of media use (such as believing it to simply be procrastination) restrict the extent to which such activities contribute to recovery [34,35], and enjoyment of the media activity (including playing digital games and watching movie clips) has been found to correlate with recovery as well as to mediate the relationship between recovery and energetic arousal [19].

Our Studies

We present 2 studies that explore the impact of digital games and mindfulness apps on post work recovery (as measured by energetic arousal and recovery experience) and the role of enjoyment. Study 1 describes a laboratory experiment that compared the effect of a digital game, mindfulness app, and nonmedia control on recovery experience and energetic arousal following a work strain–inducing task.

Study 2 was an in-the-wild field study, taking place over a 5-day period in which workers either played a digital game or used a mindfulness app after work, again comparing changes in energetic arousal and differences between the groups in recovery experience. Enjoyment of the activity was also measured in both studies.

Methods

Study 1: Laboratory Study

Study 1 aimed to test the following hypotheses:

> *H1: The use of a digital game following a work task will be associated with a greater improvement in recovery (as measured by energetic arousal) and higher recovery experience than a mindfulness app that, in turn, will be associated with greater recovery than a nonactivity condition.*
>
> *H2: Enjoyment of the activity will be associated with improved recovery.*

Participants

A total of 45 participants (26 female) aged 19 to 36 years were recruited, all were students at a UK university. Participants were recruited through word-of-mouth and flyers on campus and at student accommodation and were entered into a prize draw to win £25 Amazon vouchers.

Design

The study was a mixed-design laboratory-based experiment exploring the change in recovery (inferred by energetic arousal scores) before and after taking part in 1 of the 3 break time activities (a digital game, mindfulness app, or nonmedia activity) following a work task aimed at inducing a need for recovery. In the nonmedia activity control condition, participants were told they had no activity but were provided with a fidget spinner for use at their own discretion. An additional dependent variable was recovery experience, measured after the break activity was completed.

Materials

Work Task

The work task was intended to create a need for recovery. On the basis of previous successful attempts at inducing work stress [36,37], the task involved a series of mathematical equations that were delivered and completed in an interactive PowerPoint presentation. Participants completed 10 arithmetic problems, shown as a sequential series of numbers, which took 15 min.

Break Tasks

In the digital game condition, the participants played *Block! Hexa Puzzle*, a digital puzzle game. This was selected as it is an easy game to play regardless of the participant's previous experience, which has been identified as an important factor when testing digital games in terms of recovery [19].

In the mindfulness app condition, participants followed a 10-min mindfulness exercise from the app named *Headspace*. This app was again selected for its simplicity and clear instructions, meaning that participants could undertake the activity regardless of experience.

For the control condition, there was no designated media activity for the participant. In previous laboratory experiments on the effect of media on recovery, nonmedia control conditions involved sitting in a room and resting [15,19]. However, this could feel artificial or be boring for the participant and, thus, could impact recovery. Therefore, a toy called a fidget spinner was placed on the desk that the participant could use at their discretion.

Questionnaire Measures

The Activation-Deactivation Adjective Checklist (ADACL) [38] was used to measure energetic arousal as a proxy for recovery (as in the studies by Reinecke et al and Rieger et al [14,19,39]). This measure asks the participants to report to what degree they are feeling a series of emotional states, such as *energetic* and *tired*. Participants answered on a 4-point Likert-style scale. This measure was administered before the work task (T1), after the work task (T2), and after the intervention (T3), and it included 4 subscales: energy (mean alpha=.79), tiredness (mean alpha=.79), tenseness (mean alpha=.71), and calmness (mean alpha=.76). Energetic arousal was calculated by reverse scoring the tiredness subscale and summing this value with the energy subscale. Responses were not collected for 1 item of the ADACL (*drowsy*) because pilot testing suggesting this term was not understood and, therefore, to calculate the necessary scales, the responses for the most highly correlated item (*tired* [40]) were double weighted.

The recovery experience scale was used to measure recovery across the 4 recovery experiences [4], namely, psychological detachment (alpha=.83), relaxation (alpha=.92), control (alpha=.88), and mastery (alpha=.65). It contained 16 questions across the 4 dimensions for recovery, rephrased to refer to the activity as in the study by Reinecke [17] (eg, “When I [did the activity], I forgot about the work task”). The participants answered on a 5-point Likert-style scale.

Enjoyment was measured as in the previous study [19] with a 5-item scale, asking participants how much they agreed with statements such as, “[The activity] was fun” (alpha=.90). Participants answered on a 5-point Likert scale.

Basic demographic information was collected in the final questionnaire.

Procedure

The participants were asked if they used mobile games or mindfulness apps on their phone and were allocated to the condition they had no experience to avoid a confounding effect of previous experience. If participants had no experience of either, they were randomly allocated to a condition.

The first ADACL measure (T1) was administered through Qualtrics, a Web-based survey service. Once this was completed, the participants were presented with the work task through PowerPoint in presentation mode, which took 15 min. This task aimed to ensure that all participants were experiencing a need for recovery that had the potential to be reduced by the interventions. The participants then proceeded to complete the second administration of the ADACL (T2).

For the game condition and the mindfulness app condition, the participants were given a smartphone with the activity preloaded. For the control, the participants were given a fidget spinner that they were told could be used at their discretion. The participants were told that the break activity intervention would take 10 min. Once the break was over, the following T3 measures were taken: final administration of the ADACL scale, recovery experience questionnaire, enjoyment measures, and demographic information.

Study 2: In-the-Wild Study

The findings from Study 1 indicated the need for an in-the-wild approach to explore how digital games and mindfulness apps might impact recovery in real-world contexts. Moreover, previous work has highlighted the importance of exploring recovery on a daily level because of common fluctuations in job demands and recovery needs [41]. Therefore, Study 2 aimed to investigate the effect of a digital game and a mindfulness app in a naturalistic setting over a 5-day period. On the basis of the existing literature and the results of Study 1, the following were hypothesized:

> *H1: Participants in the digital game condition would demonstrate a significant increase in energetic arousal after performing the activity, and this increase would be significantly greater than that in the mindfulness app condition.*
>
> *H2: Participants in the digital game condition would report significantly higher daily recovery experience scores than those in the mindfulness app condition.*
>
> *H3: Enjoyment will be related to recovery experience and the change in energetic arousal before and after the activity.*

Participants

A total of 20 participants were recruited (12 female), aged 19 to 58 years. To be eligible, the participants needed to be professionals working full time (7.5 hours per day for a minimum of 4 days per week). The participants were recruited through word-of-mouth and social media and were paid with a £5 Amazon voucher. Ethical approval was provided by the University Ethical Approval Board.

Materials

Break Activities

The same break activities were used as in Study 1; *Block! Hexa Puzzle* as the digital game and *Headspace* as the mindfulness app. The game or the mindfulness app was installed on the participants’ personal smartphones. Participants in the mindfulness app condition were instructed to follow the free 5-day beginners’ program provided by Headspace.

Questionnaire Measures

The participants were initially asked for demographic information, and recovery was again measured before (T1) and after (T2) the break activity intervention by the energetic arousal scale of the ADACL, measuring the subscales of energy (mean alpha=.84), tiredness (mean alpha=.92), tenseness (mean alpha=.81), and calmness (mean alpha=.71). The energetic arousal score was again calculated by adding the energy subscale to the reverse-scored tiredness subscale.

Recovery was also measured after the break activity by the recovery experience questionnaire [4], including the 4 recovery experience subscales: psychological detachment (mean alpha=.85), relaxation (mean alpha=.84), mastery (mean alpha=.75), and control (mean alpha=.90). Enjoyment was also assessed with the same measures as the laboratory experiment (mean alpha=.83).

Procedure

The participants were first asked if they already played digital games or used mindfulness apps, and if so, how often. They were then assigned to the activity that they did not have experience in. This was to ensure a similar level of experience across participants in each condition. The participants received guidance on installing the apps, and how and when to use them on each day of the experiment.

On each of the 5 days, when first arriving at home, the participants completed the T1 survey (the first administration of the ADACL measure). A prompt was sent via email to remind the participants to do so at the time they reported to arrive home. The participants then undertook the break activity for 10 min before being prompted via email to complete the T2 survey, comprising the second ADACL and the recovery experience measures.

When all 5 days of the activity had been completed, a semistructured interview was held over the phone or on the Web to understand the participants' experiences. The interviews took approximately 10 to 15 min.

Results

Study 1: Laboratory Study

Manipulation Check

To identify whether the work task successfully created an additional need for recovery, energetic arousal at T1 and T2 was compared. A data collection error meant that T1 data were not available for 4 participants, so the analysis was conducted on the remaining 41. The mean energetic arousal scores and SDs can be found in Table 1. A paired-samples *t* test found no significant differences between energetic arousal scores at the 2 time points (t_{40}=−.037; P=.97), indicating that the work task had not succeeded in creating an additional need for recovery. However, examination of the scores suggests that our participants started with lower energetic arousal than those in previous studies (eg, Reinecke et al [19] report prework task scores between 26.11 and 27.92) and that the T2 scores observed were similar to those following a successful work task (Reinecke et al [19] report post work task scores between 23.66 and 26.72). This suggests that participants were starting this study with a greater need for recovery than the participants in other studies and also started the break activity with similar levels. There were also no significant differences between the 3 conditions at T2, meaning that participants in all conditions started the intervention with equivalent levels of recovery ($F_{2,42}$=.218; P=.81).

Analyses

Hypothesis 1

The first hypothesis was that the use of a digital game following a work task would be associated with greater recovery than a mindfulness app, which, in turn, would be associated with greater recovery than the nonactivity condition. Recovery was measured by energetic arousal administered at T2 (after the work task) and T3 (after the break activity) and the recovery experience scores administered at T3. The analyses for each dependent variable were conducted separately.

Energetic arousal increased in the digital game condition between T2 and T3, with that of the other conditions decreasing between these time points (Figure 1). A 3×2 mixed analysis of variance (ANOVA) was conducted, with energetic arousal at T2 and T3 as within-subjects factors and condition as the between-subjects factor. There was no significant effect of condition ($F_{2,42}$=.29; P=.75; η^2=.01) and no overall effect of time ($F_{1,42}$=.22; P=.64; η^2=.01). However, there was a significant interaction between time and condition ($F_{2,42}$=3.76; P=.03; η^2=.15), suggesting the degree of change between T2 and T3 differed according to the condition. Follow-up post hoc analyses on the degree of change between T2 and T3 indicate that this significant interaction is mostly owing to the differences between the digital game and control conditions (t_{28}=2.72; P=.01), and to a lesser extent, between the digital game and the mindfulness conditions (t_{28}=2.04; P=.05). There were no differences between the mindfulness and control conditions (*t* 28=0.62; P=.54).

A 1-way ANOVA was used to investigate the differences in recovery experience subscales (all taken at T3) and total score across the conditions. No significant differences between the conditions were identified (see Table 2 and Figure 2).

Hypothesis 2

The second hypothesis was that the enjoyment of the activity would be associated with improved recovery. Although there were no differences between the conditions in enjoyment ratings ($F_{2,42}$=1.47; P=.24), a Pearson correlation identified that enjoyment was significantly, positively correlated with recovery experience (r=.69; P<.001; see Figure 3), including all subscales except mastery (see Table 3).

Table 1. Mean energetic arousal scores (and SDs) across the 2 time points.

Condition	Time 1 (before work task), mean (SD)	Time 2 (after work task), mean (SD)
Digital game	26.15 (8.14)	23.40 (6.80)
Mindfulness	24.31 (5.68)	24.33 (9.15)
Control	23.93 (6.40)	25.40 (8.74)

Figure 1. Mean energetic arousal scores for each of the 3 conditions at Time 2 (after the work task) and Time 3 (after the break activity).

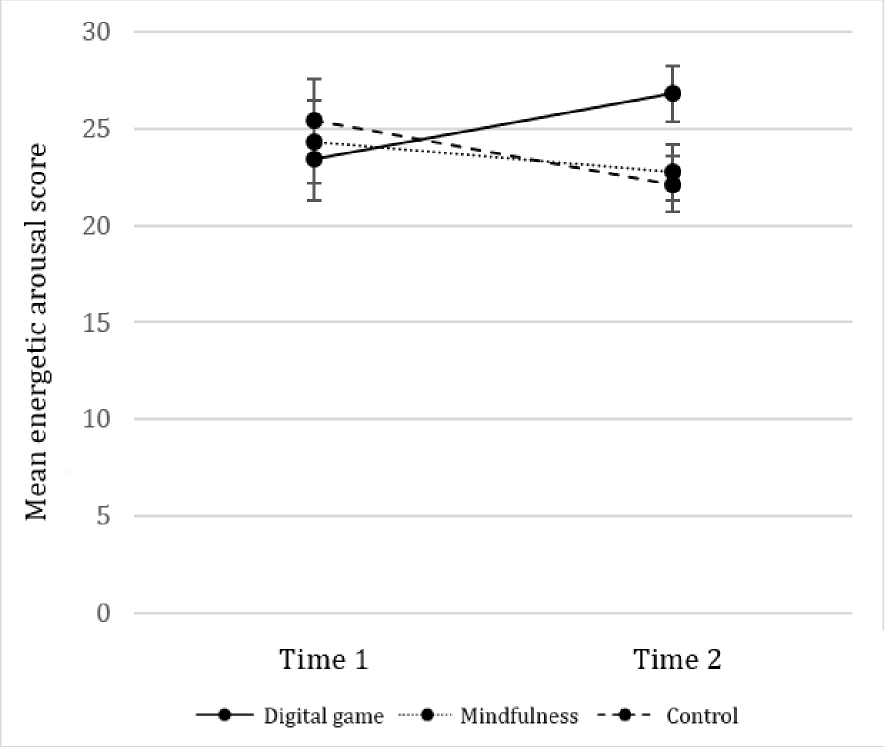


Table 2. Results of a 1-way analysis of variance comparing the 3 conditions on recovery experience subscales and total score.

Measure	*F*	η^2	*P* value
Psychological detachment	0.30	.01	.74
Relaxation	0.90	.04	.42
Mastery	1.31	.06	.28
Control	0.43	.02	.65
Recovery experience total	0.01	.00	.99

However, the difference in energetic arousal between T2 and T3 was not correlated with enjoyment (*r*=.241; *P*=.11), indicating that although those who were more recovered rated the activity as more enjoyable, greater enjoyment did not result in an increase in recovery outcomes.

Study 2: In-the-Wild Study

To retain the variations between the individual days within participants, and to examine the change over time, a model comparison approach [42,43] was used. Linear mixed-effects models were constructed with recovery measures (recovery experience and energetic arousal) as the dependent variables, condition and day as fixed effects, and participant as a random effect.

A total of 3 models were fitted for each dependent variable following Singer and Willett [44]. The first was an unconditional mean model, which operated as the control model. This model represents the null hypothesis that there is no change in the dependent variables over time and that there is no effect of condition. The second model was an unconditional growth model, representing the hypothesis that there is a change in the measure over time but that there is no effect of condition on the measure. By comparing the proportion of reduction of error (PRE) in this model with the PRE in model A, we can test if the measure is changing over time in days. Finally, the third model was a conditional growth model, representing the hypothesis that there is a change in the measure over time, and that there is an effect of condition on measure. Comparing this model with model B tests if the growth of the measure is affected by the data condition.

All models used ordinary least squares regression as this is the most parsimonious [44]. Maximum likelihood estimation was used because of the models having different numbers of fixed-effect terms [44,45].

Hypothesis 1

The first hypothesis was that participants in the digital game condition would demonstrate a significant increase in energetic arousal after performing the activity and that this increase would be significantly greater than that in the mindfulness app condition.

Figure 2. Mean scores for the recovery experience subscales across the 3 conditions.

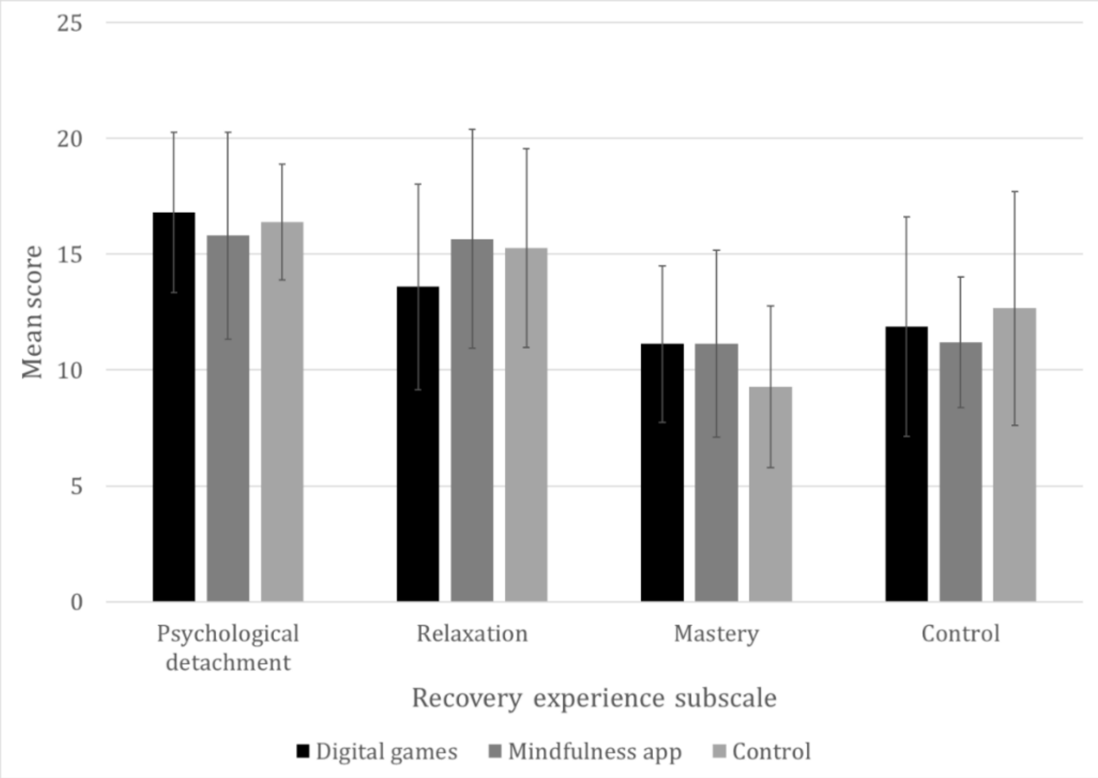


Figure 3. Scatterplot showing the correlation between enjoyment of the activity and Recovery Experience scores.

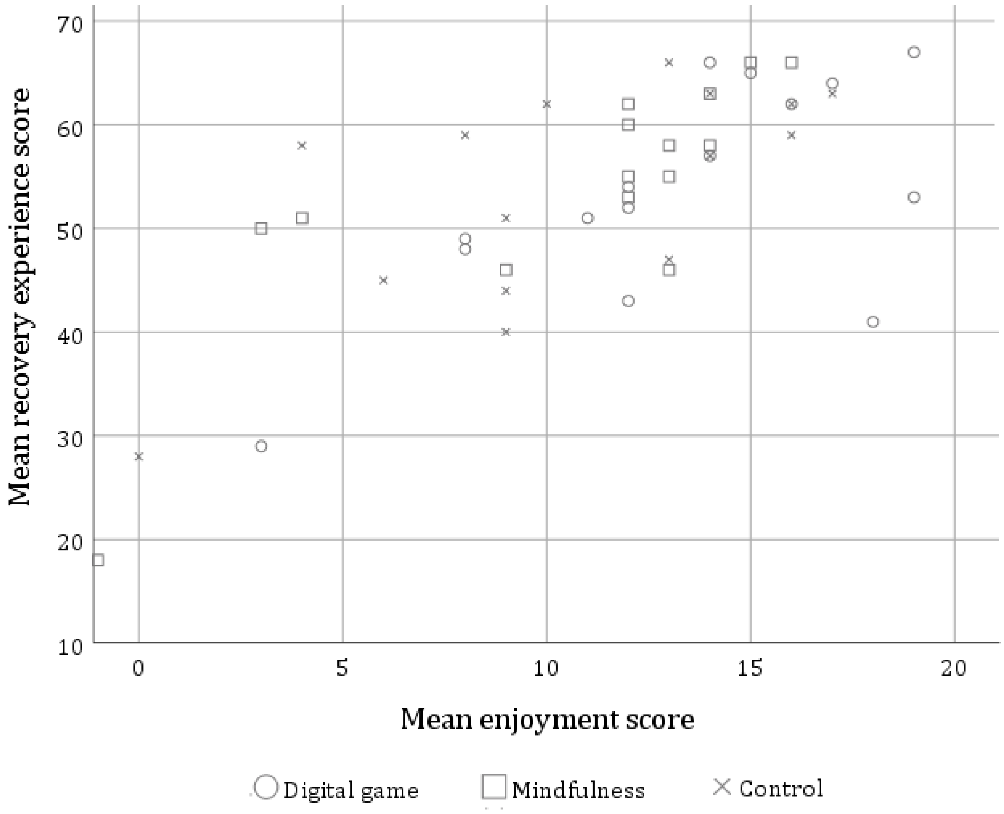


Table 3. Correlation coefficients between reported enjoyment and recovery experience subscales.

Measure	Enjoyment	*P* value
Psychological detachment	.584	<.001
Relaxation	.635	<.001
Mastery	.215	.16
Control	.421	.004
Recovery experience total	.691	<.001

To investigate the potential impact of the break activity on energetic arousal, the 3 models were constructed with the change in energetic arousal between T1 and T2 as the dependent variable. The conditional growth model was not found to be a significantly better fit for the data than the unconditional growth or unconditional mean models, indicating that there was no significant relationship between energetic arousal scores and either condition or day of the study.

Hypothesis 2

The second hypothesis was that participants in the digital game condition would report significantly higher daily recovery experience scores than those in the mindfulness app condition. The conditional growth model had a lower Akaikike Information Criterion (AIC) than the unconditional growth model (λ_2=9.2; *P*=.01), which, in turn, had a lower AIC than the unconditional mean model (λ_3=21.74; *P*<.001), indicating that the conditional growth model was a significantly better fit for the data.

Sequential (type 2 sum of squares) *F* tests were performed on the conditional growth model, using the Satterthwaite approximations for degrees of freedom and sigma adjusted to provide more conservative Restricted Maximum Likelihood-like results. The main effect of condition was not significant ($F_{1,18}$=1.93; *P*=.18) and the main effect of day was not significant ($F_{1,18}$=.00; *P*=.97). However, there was a significant interaction between condition and day ($F_{1,18}$=9.97; *P*=.01); the parameter estimates indicated that recovery experience scores increased over time in the digital game condition but decreased over time in the mindfulness app condition.

In line with study 1 and previous literature, we also included an analysis of the recovery experience subscales. The 3 models were constructed for each subscale, which was compared and then analyzed using sequential *F* tests, as before. The model comparisons indicated no significant relationships for the control or psychological detachment subscales, although the conditional growth model was a significantly better fit than the other models for the latter (λ_2=6.10; *P*=.05), suggesting that the lack of relationships with condition and day maybe because of ceiling effects. However, the significant interaction between condition and recovery experience was evident in the mastery ($F_{1,18}$=5.99; *P*=.02) and relaxation subscales ($F_{1,35}$=14.32; *P*<.001). For the relaxation subscale, there was also a significant main effect of condition ($F_{1,25}$=9.40; *P*=.01). Relaxation increased over time for the digital game condition and decreased for the mindfulness condition. In addition, being in the mindfulness condition conferred a mean of 3.85 units more than being in condition 1; those in the mindfulness condition started with higher relaxation scores than those in the digital game condition, but their relaxation scores dropped as that of those in the digital game conditions increased.

Hypothesis 3

The third hypothesis was that enjoyment will be related to recovery experience and the change in energetic arousal before and after the activity.

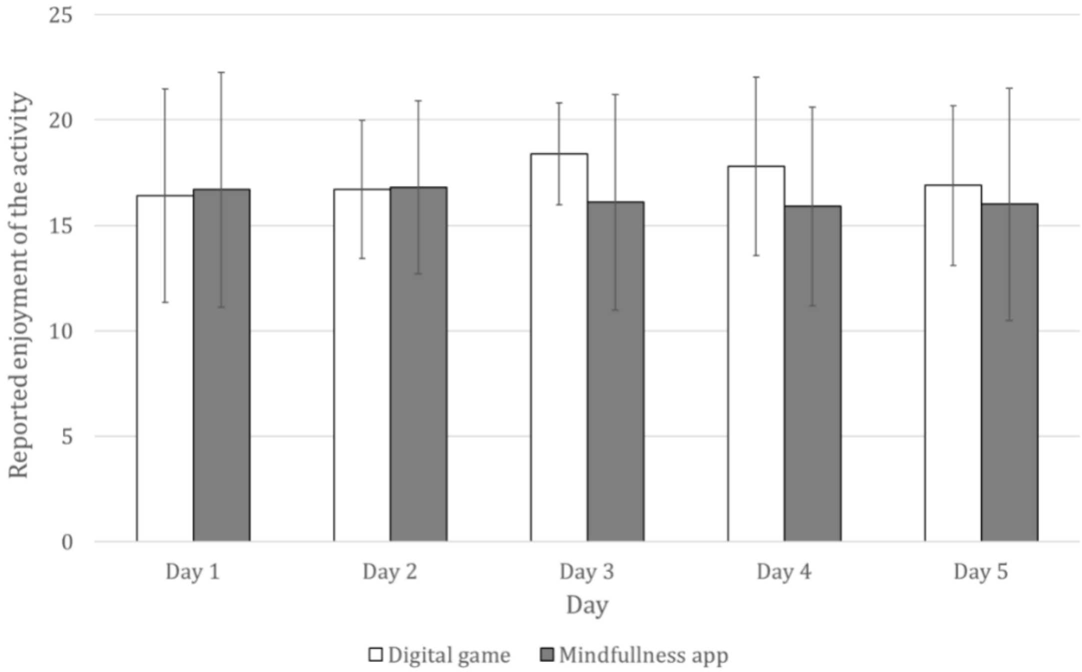
The average enjoyment score (averaged across the 5 days of the study) was positively correlated with the average recovery experience score (*r*=.596; *P*=.01), relaxation (*r*=.657; *P*=.002), and mastery (*r*=.612; *P*=.004) but not with psychological detachment (*r*=.323; *P*=.16) or control (*r*=.278; *P*=.24). It was also positively correlated with the change in energetic arousal before and after the activity (*r*=.515; *P*=.02).

There were no significant differences between the conditions on either a daily level or in the average enjoyment score (see Figure 4). However, the digital game condition demonstrated a different pattern of correlations compared with the mindfulness condition. For instance, only in the digital game condition was the correlation between enjoyment and recovery experience significant (*r*=.738; *P*=.02), with no correlation in the mindfulness condition (*r*=.52; *P*=.13). In the digital game condition, there were also significant correlations between average enjoyment and psychological detachment (*r*=.672; *P*=.03) and mastery (*r*=.676; *P*=.03), whereas, in the mindfulness condition, there was only a significant correlation between enjoyment and the relaxation subscale (*r*=.799; *P*=.01). Similarly, only for digital games was there a significant association between enjoyment and the *change* in energetic arousal before and after the activity (*r*=.46; *P*<.01), with no such association in the mindfulness condition (*r*=.23; *P*=.11). This indicates that only in the digital game condition was it related to the *degree of change* in recovery as a result of taking part in the activity.

Qualitative Analysis

The interview transcripts were analyzed using thematic analysis [46] with a bottom-up approach. A total of 5 themes emerged, which were organized into 3 core themes: *detachment and restoration* (comprising of *detachment versus interruption* and *restoration and relaxation*), *fluctuations and differences* (comprising *daily variations* and *personal preferences*), and *routine and scheduling*.

Figure 4. Reported enjoyment across the 5 days of the study and across the 2 conditions.



Detachment and Restoration

The *detachment and restoration* theme relates directly to the subjective experiences of recovery. The participants from the 2 conditions described their experiences in relation to detachment and restoration very differently.

This core theme contains 2 subthemes, *detachment versus interruption* and *restoration and relaxation*, combined because of the connection between the former as an experience and the latter as an outcome.

Detachment Versus Interruption

The 2 groups differed in the ways in which they discussed *detachment versus distraction*. For those in the digital game condition, part of the experience was a feeling of mental disengagement from the stresses of the workday, something that was referenced by all participants in this condition:

> *Even if you had a lot racing through your mind after a busy day at work, it was a good way to actually switch off from that, and once you'd finished the game, you felt as if you were actually relaxed and actually out of that work zone.* [P2]

This appeared to help participants in this condition to transition between work and home contexts:

> *I felt like I was restarted, you know, like a computer… It was such a short period of time, and then I felt very refreshed, and then I didn't think about work for the whole evening.* [P20]

Although this experience was not universal (P7 reported only minimal distraction with the digital game), it was in contrast to those in the mindfulness app condition. Only 1 of the mindfulness app participants mentioned renewed focus postactivity:

> *It's like okay, you've put that work behind you, but now you can get on with what other stuff you want to do, so it is that divide.* [P3]

When detachment was mentioned by those in the mindfulness condition, it was more in terms of physically taking time away from other activities and not as a psychological process:

> *It was taking time out I suppose. I guess it's a bit like going to have a facial or something.* [P5]

Restoration and Relaxation

A related theme that emerged from the data was *restoration and relaxation*, as many participants described their feelings after the activity in terms of arousal and energy. Participants in the digital game condition reported mixed outcomes. For example, 1 participant described feeling more relaxed after playing the game but also more tired (P11). A number of participants reported that they found the game calming, even if they did not enjoy the activity:

> *It was calming in a way, like I think because it's quite a monotonous type of activity.* [P9]

Conversely, other participants reported feeling more energetic after the digital game:

> *When you're tired from work, it just gets you a bit more alert.* [P15]

Within the mindfulness app condition, a number of participants described feelings of calm and relaxation but also sometimes tiredness:

> *I'd say all days I was more tired. But, definitely a few days it made me feel calmer. It was on like a scale.* [P6]

Other participants appreciated the tiredness that the mindfulness app encouraged as it helped with sleeping or bringing down energy levels when they were unwelcomingly high:

> *Sometimes if I have like a late football match and I get back late, sometimes I've still got the adrenaline going all over my body before I go to bed, and it takes a while to go to sleep. So, I think [the mindfulness app] kind of did help as well, so that was nice.* [P8]

Variations

The second core theme that emerged was related to variations; the participants were aware that the experience of performing both of the activities was not uniform, and the events of the day, moods, and personal preferences could impact their outcomes. This theme incorporates 2 subthemes: *daily differences* and *personal preferences.*

Daily Differences

Supporting the day-level approach of the quantitative analysis, 9 participants commented on daily variations in their experience of the activities. Several participants in both conditions commented that they found the activity more beneficial when they returned from a busier or more stressful day at work than on more calm days:

> *It depended on the day I'd had at work…I felt on the days that work was very busy I got a lot more out of the game.* [P2, digital game]

> *If [the day] was more stressed, I might have been slightly more resistant to relax, but it definitely helped…probably helps more on the stressful days.* [P3, mindfulness app]

However, there were exceptions with 2 participants who used the mindfulness app. For example, P6 reported that they found the activity more calming after a less stressful workday.

Personal Preference

There was also an appreciation that the effectiveness of the activities was not only dependent on the daily variations but also on differences in personal preference. Several participants reported that they did not enjoy the game ("I'm not really a gamey person." [P12]), and they felt that this hindered potential benefits. The participants in the mindfulness app did not report a predisposition against mindfulness apps from the beginning as, often, this was their first time in trying the activity. However, through the study, some did learn that they did not enjoy using mindfulness apps.

Some participants mentioned that they felt they could get similar recovery benefits from other activities than those used in the study, choosing ones that they enjoyed more:

> *If I was going to do a game…it would be more kind of word based or something like that.* [P12]

Only participants in the mindfulness app condition reported that 10 min was too long for such an activity:

> *I think I would have enjoyed it if it was less time…I didn't enjoy it in the first place probably because it was so long, or it felt long.* [P6]

Scheduling and Routine

Some of the reported benefits of the activities were not so much to do with the game or app itself but more because of having a specific task scheduled for a particular time. For example, although participants said that after the activity, they "felt like doing something" (P15, digital game condition), further questioning indicated that it was more to do with the structure that the activity provided:

> *I think it was good to have a set routine when I got home that I had to do something instead of just kind of like sitting down and not really having a plan. It focussed me a little bit more, to know that when I got home, sat down, did the game, and then I moved on with the rest of my day then.* [P11]

Rather than continuing playing the digital game after the end of the study, 1 participant (P11) instead continued the routine, replacing the game with a walk, further emphasizing the role played by the schedule over the activity.

Discussion

Principal Findings

Study 1: Laboratory Study

Study 1 aimed to explore whether a digital game or a mindfulness app provided greater recovery outcomes than a no-activity control following a recovery-inducing work task. The digital game condition significantly improved energetic arousal between T2 and T3, with the mindfulness app and no-activity conditions showing a slight decrease. However, there were no significant differences between the conditions in the recovery experience. Enjoyment was positively correlated with recovery experience, but it was not related to the change in energetic arousal, suggesting that those who were more recovered reported the activity as more enjoyable, but the level of enjoyment itself did not impact recovery. A notable caveat is the lack of successful manipulation of recovery. One possibility is that this was because of the nature of the work task; although similar arithmetic tasks have been shown to induce work stress in previous studies [36,37], it has been argued that fast-paced tasks are more effective at reducing energetic arousal levels [47]. For instance, some previous work has instead used tasks such as highlighting specific letters in texts (eg, the study by Reinecke et al [19]). However, another explanation for the lack of an effect is that our participants had lower baseline energetic arousal than in previous studies, which meant that an additional reduction in these scores was not possible. This is supported by the discovery that the observed time 2 energetic arousal scores were comparable with those from studies in which the work task was successful in inducing a need for recovery, suggesting that participants were still starting the break activity with depleted resources. These relatively low levels of energetic arousal, coupled with the discovery that the effect of the digital game was in the opposite direction to that of the other conditions, indicate that the digital game may still be restorative in a manner that the other conditions are not. The lack of significant differences between the conditions in energetic arousal following the work task is also reassuring, as even with the potentially polarizing effect of the work task, participants in all 3 conditions were beginning the break activity with a similar overall level of energetic arousal.

This study also found no difference between the conditions in terms of recovery experience scores. Previous research suggests that digital games are more effective in promoting recovery than nonmedia or noninteractive activities and that the recovery experience measure tends to reflect the energetic arousal scores [14,15,19]. As the wording of the recovery experience measure emphasizes feeling differently following the break activity intervention, the score could have been impacted by the unsuccessful recovery manipulation to a greater degree than the energetic arousal measure, for which there is greater variation and less of a focus on comparative experiences. Taking these results with those of Study 2 which was able to avoid these issues is therefore important in gaining a full understanding of the impact of digital games and mindfulness apps on recovery.

Study 2: In-the-Wild Study

Study 2 aimed to explore the impact of a digital game and a mindfulness app in a real-world context over 5 days. It was predicted that those in the digital game condition would show a greater increase in energetic arousal scores following the activity compared with those in the mindfulness condition and that those in the digital game condition would also demonstrate higher recovery experience scores. Enjoyment was predicted to be related to both the final recovery experience scores and the change in energetic arousal between T1 and T2, indicating that enjoyment underpins the relationship between activities and recovery. Multilevel modeling identified that there were no differences between the conditions in terms of the degree of change in energetic or tense arousal before and after the activity. However, there was a difference between the 2 conditions in the pattern of recovery experience; in the mindfulness app condition, recovery experience scores (particularly relaxation and mastery) steadily decreased during the 5 days of the study, whereas in the game condition, they increased. Therefore, although there was no evidence of either activity impacting recovery on a daily level, there appeared to be a cumulative, positive effect of the digital game.

Follow-up interviews allowed further exploration of the subjective experiences of the activities, with the core themes of *detachment and restoration* (comprising *detachment versus interruption* and *restoration and relaxation*), *fluctuations and differences* (comprising *daily variations* and *personal preferences*), and finally, *routine and scheduling* emerging from the interview data. Differences between the conditions in opportunities for detachment from work were particularly relevant and shine some light on the quantitative findings concerning the cumulative effect of digital games on recovery experience scores.

The discovery that there was no daily effect of the activities on recovery, particularly in relation to the change in energetic arousal scores, runs somewhat counter to previous studies. Laboratory studies have shown that even after short work tasks, digital games can successfully impact energetic arousal scores to a greater degree than nonmedia activities [15,19]. The failure to replicate these findings may simply be because of the more complex and less controlled environment of in-the-wild studies, the less uniform experience of a day's work in comparison with a specified work task, or the differences in timings between work and the completion of the intervention. Work stress and subsequent recovery needs have been argued to vary from day to day [41], making a clear-cut relationship between activities and recovery outcomes in the absence of any other influences unlikely. Nonwork leisure activities have been said to impact individuals on a daily level in a manner that prevents the buildup of work stress, which, in turn, manifests in poor health outcomes [41]. Therefore, the discovery of a cumulative effect, but not a daily effect, of digital games is not wholly surprising and is in accordance with much of the more general recovery literature.

Alternatively, the cumulative effect of the digital game could be because of the increases in gaming skills over the experimental period; previous research has found that greater gaming skill is positively related to the degree of mood repair experienced after playing a digital game [48]. This would suggest that the more our participants played the game, the more they improved, which in turn had a larger impact on their mood. However, it is difficult to know whether such an effect would occur for a simple game such as *Block! Hexa Puzzle.*

The negative pattern of recovery in the mindfulness app condition over the course of the study was particularly interesting and surprising. It is possible that this pattern is simply because of the need for recovery increasing during the working week; however, without a control group or baseline, it is not possible to conclude whether this decline in recovery was due to the mindfulness app negatively impacting recovery or whether this pattern would have occurred as a result of passing time regardless of our intervention.

The in-the-wild interviews indicated that personal preference may have had an impact on enjoyment, supporting previous research that identified that different people can evaluate the same activity as relaxing or as a chore [49] and that individual preference could result in whether a person enjoys and subsequently recovers from an activity [10,50]. Considering that previous research has also highlighted the role of personal appraisals of the activity (eg, how beneficial or worthy they are seen to be or how much they constitute procrastination rather than a legitimate way of spending time) in promoting recovery [16,19,34], this might be an interesting route for future research. Another interesting point raised was the role of the activity as a scheduled break point and the benefits that emerged because of this rather than the activity itself. This supports previous assertions that implementing specific routines can be beneficial for post work recovery [51].

Limitations

The first limitation of this study is that the nature of the study means that participants were trusted to follow instructions and perform the activities in the manner requested, but no checks were made to ensure this was the case. This is a risk associated with many in-the-wild field studies, and the only alternative would have been to install a software to track the activities performed on participants, which would have likely reduced interest in participating.

The second is that participants were not able to choose their activity and were instead pseudorandomly assigned to one of the conditions. Although this method helps avoid the influence of possible person-level confounds, enjoyment and the subjective experience of activities are known to be important factors in recovery outcomes [33]. Consequently, it is possible that allowing participants to choose the activity they would enjoy the most would have increased the observed restorative effect. However, this would have reduced confidence in our conclusion that any differences between the conditions were in fact because of the activity and not other related variables. The lack of extreme scores for the enjoyment measure and the lack of overall differences in the score between the conditions suggest that there were no participants who reacted negatively to the activity and that, generally, the activities were seen as equally as enjoyable. Future work may wish to explore the effect of personal choice of activity on recovery outcomes.

Finally, there is the possibility of a ceiling effect for psychological detachment that prevented us from exploring the possible impact of the activities on this measure. This was suggested by the model analysis, which found that although there was no significant association between the measure and the day of the study or the condition, the conditional growth model was a significantly better fit than the other models. Future studies may wish to specifically target individuals with low psychological detachment to explore how these activities impact this measure.

General Discussion

This paper outlines 2 studies that aimed to explore whether a digital game and a mindfulness app were able to improve post work recovery. Study found that the digital game condition was the only one to significantly increase energetic arousal, although there were no differences between the conditions in terms of recovery experience. Study 2 found that although neither condition appeared to impact participants in terms of either energetic arousal or recovery experience on a daily level, those in the digital game condition demonstrated an accumulative effect on recovery experience, with scores gradually increasing over the 5 days.

The discovery that digital games have the potential to improve recovery above and beyond more passive activities is supported by previous research [14,18,19,35]. However, our support for this is somewhat tentative owing to the lack of differences between the conditions in terms of recovery experience in Study 1 (with the only differences being in relation to the degree of change in energetic arousal before and after the activity) and the lack of differences in energetic arousal in Study 2 (with differences only occurring in terms of recovery experience over time). Although both energetic arousal and recovery experience scores are intended to operate as proxies for recovery, they do so in very different ways; the energetic arousal score reflects the affective state associated with good recovery, whereas the recovery experience scale directly asks individuals to what degree the activity provides the 4 different recovery experiences. Therefore, although the strongest evidence for a positive role of digital games in recovery would be for the effect to be evident across both measures, it is not surprising to have different patterns in each. This is particularly the case considering that owing to the nature of the measures, this study focused on the change in energetic arousal and just a one-time score for recovery experience.

However, one clear conclusion across both studies is a lack of effect of the mindfulness app; the mindfulness app was not able to improve recovery outcomes in terms of energetic arousal or recovery experience scores, in the laboratory or in-the-wild. Previous research exploring the impacts of mindfulness practice in promoting psychological detachment [31] is mixed, with little other work conducted on the relationship with recovery more generally. Although it is possible that the use of mindfulness apps has positive outcomes in terms of well-being or positive affect, this study suggests no benefits in relation to recovery.

There was also a clear relationship between enjoyment and recovery. However, in Study 1, enjoyment did not correlate with the *change* in energetic arousal before and after the activity, suggesting that a more enjoyable activity did not result in greater increases in recovery. However, in Study 2, the average enjoyment rating correlated with both the average recovery experience score and the degree of change in energetic arousal before and after the activity, in line with previous research [19,32,52]. The lack of a successful manipulation of energetic arousal in Study 1 could be responsible for this discrepancy; without enough variance between pre- and postenergetic arousal scores, it is unlikely that enjoyment could improve energetic arousal to a great enough degree to result in significant correlation.

General Limitations

In addition to the limitations discussed in the 2 individual studies, there were other overarching limitations that need to be acknowledged. The first was the reliance on self-report measures as proxies for recovery. Although such measures have been used successfully in previous studies exploring the effect of digital games [15,19], future work may wish to supplement these measures with cognitive tests that are able to identify whether participants also demonstrate evidence of being cognitively recovered through calculating error rates. This study has also highlighted other interesting avenues of investigation for future research. For example, Study 2 was not able to explore any differences in the effects of the activities depending on the nature of the participants' work or the specific demands of their roles. Similarly, collecting baseline data would strengthen the conclusion that changes in recovery outcomes are attributable to the activities undertaken and not the progression of the week. Finally, measuring personal appraisals of digital game use and their perception as procrastination or a pastime would be a welcome addition to future work, considering the existing literature on how negative perceptions of media use hinder their effect on recovery [34,35].

Conclusions

Together, these 2 studies suggest that digital games may be effective in promoting post work recovery in laboratory contexts, even without the depleting effect of a work task (Study 1) and in the real world, although the effect in this case may be cumulative rather than instant (Study 2). Our qualitative findings further highlight the roles of enjoyment and personal preference (suggesting that those who enjoy digital games may benefit the most), the daily changes in recovery needs (indicating that activities may impact differently depending on the demands of the day), and the scheduled nature of the activity (suggesting that having a specific time for playing digital games could be especially effective).

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Conflicts of Interest

None declared.

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Abbreviations

ADACL: activation-deactivation adjective checklist
AIC: Akaikike Information Criterion
ANOVA: analysis of variance
EPSRC: Engineering and Physical Sciences Research Council
PRE: proportion of reduction of error

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