The Mediating Role of Digital Health Intervention (DHI) Engagement in the Relationship between Feedback Variations and Mental Well-Being

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Abstract

Background and Objective. In recent years, technological developments and limited resources to meet a global increase in demand for mental healthcare, have led to the emergence of accessible digital mental health interventions (DHIs). Despite consistent reports of effectiveness, disengagement remains the main barricade for successful eMental Health (eMH) implementation. A new personalization approach aims at testing DHI engagement as an underlying mechanism responsible for the relationship between intervention and technological factors (ITFs), such as feedback variations and intervention effectiveness. This study aimed to investigate a mediation role of DHI engagement in the relationship between feedback categories as ITFs and mental well-being as an outcome measure for intervention effectiveness in a 14-day mobile intervention.

Methods. In a pretest-posttest study design, 'The Incredible Intervention Machine' (TIIM) application was used to collect quantitative data from 153 participants with a mean age of 21.76 (SD_{age} =5.78). Participants were randomly assigned to either an in-text-only feedback condition (n=48), an in-text with a picture of an avatar condition (n=57), or a pre-recorded video of a counselor condition (n=48). DHI engagement scores were retrieved at three measurement points (T1-T3) throughout the intervention. The main effect of time was analyzed by performing an ANOVA comparing the three conditions and testing effect sizes using Cohen's *d.* Besides, simple mediation analyses were conducted to test mediation for DHI engagement on posttest mental well-being and well-being change scores.

Results. The analyses showed that total mental well-being increased significantly between pretest and posttest. No statistically significant differences between feedback conditions were found in predicting the outcome measures. Feedback variations themselves were not found to have an impact on DHI engagement and total mental well-being, thus a mediation effect of DHI engagement could not be established. Nonetheless, DHI engagement was found to be a predictor of mental well-being.

Conclusion. DHI engagement is a promising predictor for eMental health intervention effectiveness. Further testing needs to be conducted to investigate DHI engagement as a mediator. To prepare the mediation model, future research is recommended to improve the relationship between ITFs and intervention effectiveness by a multidirectional personalization approach.

Keywords: eMH, DHI engagement, micro-intervention, well-being, feedback, personalization

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Introduction

Mental health is increasingly recognized to play an essential role in achieving global development goals, exemplified by the inclusion as health priority in the 2030 Agenda for Sustainable Development Goals at the 70th session of the UN General Assembly (Izutsu et al., 2015). Mental health problems such as depression, anxiety, and alcohol and drug use disorders affect more than one in six people in the EU (OECD, 2018). The impact on those that suffer, further underlines the importance to recognize and act on this subject matter. In this connection, depression is a leading cause of disability (Friedrich, 2017) and the resulting disease burden of mental illnesses causes about 7% of all global burden of disease (Rehm & Shield, 2019). 27% of adults worldwide report mental health issues to be the biggest health problem for people in their country (Ipsos, 2018). Besides this obvious health burden, the total costs of mental illnesses are estimated to be over 600 billion euros – or more than 4% of the Gross Domestic Product (GDP) in the 28 EU countries (OECD, 2018). A large part of these costs can be attributed to lower labor participation and productivity of people affected by mental illness, but also higher spending of social insurances and direct expenditure on health care. Despite the relevance to provide mental health services, the access to traditional expert-level care is limited. Responsible for this barrier are several factors such as shortages in staff and money (Krausz et al., 2019). In the Netherlands alone, patients spend on average 13 weeks on the waiting list to receive mental healthcare (Nederlandse Publieke Omroep, 2018). Other barriers to mental healthcare supply are population specific factors being attitudes against seeking treatment (Andrade et al., 2014), and cross-cultural differences between patient and health-care provider such as language (Mucic et al., 2016). In light of the barriers to demand immediate, affordable, and population-specific mental health support, innovations in information and communication technology (ICT) progressively emerge and aim to improve mental healthcare accessibility (Lal & Adair, 2014).

e-Mental Health: Opportunities and Advantages

Increasing use of computer and communication technology reflected by growing smartphone ownership (Poushter, 2016) and internet access (Hilty et al., 2018), create opportunities for those that have no accessible alternatives to receive health support (Torous et al., 2019; Oshima et al., 2021). A relatively young field that can be contemporarily referred to as ‘e-Mental health’ (eMH) addresses these opportunities and utilizes ICT innovations for evidence-based interventions that aim to “treat and prevent mental health disorders” (Schueller, 2018, p.91). The development efforts of eMH interventions adapt to- and grow with the availability of consumer-oriented technologies. Some examples of types of e-Mental health interventions are psychoeducational webpages, wearable devices such as smartwatches (Smuck et al., 2021), virtual reality, or smartphone applications. These different formats of e-Mental health platforms come with context-specific application areas, which allows users to choose from a pool of options.

Areas of Application: Contexts and settings of use

The wide range of eMH types offers a flexible implementation. In non-clinical settings, individuals can use their equipment (e.g., smartphone), to independently access mental healthcare. For example, users who are separated by time and space can connect over the internet and use forums to exchange anonymous peer support with others that have similar presenting issues (Moock, 2014; Hanley et al., 2019).

In clinical practice, e-Mental health programs may function as a complement to-, or replacement for traditional face-to-face therapy. In a complementary effort, e-Mental health care services are provided as a combination of web-based and traditional face-to-face treatment components. The so-called blended concept (Ebert et al., 2018) benefits from technologies in that they can take over treatment components that do not necessarily require the face-to-face guidance by a psychotherapist. For example, online-administered psychoeducation can be employed, as well as between-session exercises, which allows intensified care during face-to-face sessions (Sander et al., 2017; Ebert et al., 2018). Also, blended care offers an approach to users for whom pure traditional forms of mental healthcare might not be an appealing alternative. The blended approach option may give patients an increased take on self-management while keeping face-to-face contact and thereby the advantages of a high-quality therapeutic alliance (Kip et al., 2020).

As a replacement, web-based interventions may also benefit from time and geographical independent access to evidence-based care provision. This mode of delivery can be useful for those that are limited in mobility or populations that do not find time during working hours. Also, such approaches could address people who are dissatisfied with conventional services, those that desire anonymity, or individuals who feel stigmatized (Lal & Adair, 2014). Specifically self-managed smartphone applications can be conveniently implemented into users' daily lives and have the potential to provide reductions in various symptomologies such as depression (Firth et al., 2017) and anxiety (Ivanova et al., 2016), compared to people in waiting list conditions. Moreover, these smartphone interventions can produce equal treatment outcomes compared to interventions with therapist guidance.

Although there are concerns that a steep increase of ICT innovations comes with difficulties to ensure homogenous quality standards (Ferreira-Lay & Miller, 2008), state-of-the art research finds eMH may contribute to a more accessible, cost-effective delivery and high quality of care (Kip et al., 2020).

Limitations to e-Mental Health Effectiveness

Despite the promises and successes of e-Mental health interventions at treating and preventing mental disorders, there is less evidence demonstrating their efficacious implementation into routine practice. A main issue to the effectiveness of e-Mental health interventions is nonadherence. Often in digital health interventions, participants do not use a technology as intended by developers (Kelders et al., 2012). Examples are participants not completing all components of an intervention, or not using a step counter app on a daily basis. A systematic review by Donkin et al. (2011) found associations between number of logins and physical health intervention outcomes, suggesting the frequency of use to be representative of the participants' willingness to use a technology. Research has shown that there is a 'dose-response' relationship: the more an intervention is used, the more positive effects are experienced by its users (Donkin et al., 2011; Yeager et al., 2018). However, the research paper by Donkin et al. (2011) also highlights contradictory findings for interventions targeting depression and anxiety. Here, measures of logins, time online, and self-reported activity completions did not predict the outcome measures. It has been argued that this has to do with varying conceptualizations and measurements of adherence, but also that participants' involvement with the intervention content leads to change, rather than a mere tendency to adhere by the frequency and duration of using a program. In this regard, it has been hypothesized that motivations of participants to use a technology might equate to better results compared with the frequency or duration of use (Kelders, van Zyl, and Ludden, 2020).

Engagement as a Predictor for Effectiveness

When looking at the reasons behind digital health intervention (DHI) use, the concept of engagement emerges as a predictor for effectiveness (Yardley et al., 2016; Perski et al., 2016; Kelders, van Zyl, and Ludden, 2020). Engagement broadly defines as involvement or occupation with something that leads to a positive outcome (Kelders, van Zyl, and Ludden, 2020). In digital and e-Mental health, research consistently reports that user feelings of involvement and identification with an intervention are associated with enhanced intervention effectiveness (Donkin & Glozier, 2012; Kelders, 2015; Kelders, 2019). Thus, designers are challenged to create e-Mental health interventions that are not only usable and effective, but also “immerse consumers and users in its content” (Kelders, van Zyl, and Ludden, 2020, p.2). However, addressing engagement in eMH requires a shared understanding of the concept. Until recently, a shared conceptualization and operationalization of engagement within the context of DHIs was lacking (Kelders, van Zyl, and Ludden, 2020). A review on engagement in digital health interventions found, that a majority of research limits its understanding of engagement to behavior, synonymous with the usage of a DHI. Hereby, the amount, depth, duration, and frequency of use are listed as attributes. However, this purely behavioral conceptualization is prone to being confused with adherence (Short et al., 2018) and is claimed to be incomplete. Field research consistently suggests a multidimensional view of engagement, with a conceptualization in terms of behavior and subjective experience which is composed of cognitive and emotional states: attention, interest and affect (Yardley et al., 2016; Perski et al., 2016; Kelders, van Zyl, and Ludden, 2020).

Based on inconsistent and incomplete engagement measurement efforts in the past, as well as the proposal for a shared understanding of engagement as a multifaceted concept, Kelders and Kip (2019) developed a scale to measure the entire DHI engagement complex. Three components were identified to compose engagement, namely behavior, cognition, and affect. The nine-item Twente Engagement with Ehealth Technologies Scale (TWeets) captures the facets of each component and promises to be a valuable instrument to study the relationship between DHI engagement and intervention effectiveness (Kelders, Kip, & Greeff, 2020). To illustrate, individual constitutions of engagement (e.g., low behavioral component) can inform designers to make design and content choices to shape an individual’s experience, feelings, and behavior towards the intervention (Niedderer et al., 2017; Kelders, van Zyl, and Ludden, 2020).

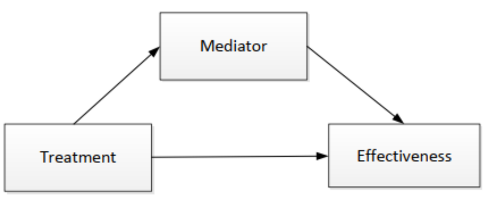
Burley et al. (2020) characterize such a sensitivity- and adaption to individual user characteristics instead of a ‘one-size-fits-all’ treatment, as a personalized approach towards eHealth design. Besides accounting for individual constitutions of engagement, eMH development can adjust other intervention and technological factors (ITFs) to suit individual user demands, and thereby facilitate DHI outcomes. For example, a meta-analysis showed that various mental health outcomes can be positively influenced by personalized feedback given on exercises in app-supported smartphone interventions (Linardon et al., 2019).

Despite a promising personalization approach towards eMH, two crucial issues in current personalization efforts can be identified. First, the immense variety of combinations of intervention factors complicate the process for designers to identify- and implement predictors for individual effectiveness. For example, variations in feedback given to participant responses can have disparate effects on different intervention users. Hereby, research is inconclusive whether personal face-to-face feedback or automated feedback messages are more appropriate in form and content (Baumeister et al., 2014; Köhle, 2016). On the one hand, research has consistently found that counselor or clinician support represents an essential facilitator for engaging intervention design development (Samoocha et al., 2010; Brouwer et al., 2011; Mohr et al., 2011; Kelders et al., 2012; Baumel & Kane, 2018). Studies have also shown a successful impact of conversational agents within self-guided digital interventions (Bickmore et al., 2010; Ly et al., 2017), suggesting the promotion of a therapeutic alliance between the user and the technology (Cavanagh & Millings, 2013; Holter et al., 2016; Baumel et al., 2017). On the other hand, there is support that nonguidance contact (e.g., encouragement texts) can have significant benefits in the absence of support by a professional counselor (Talbot, 2012; Titov et al., 2010).

The second issue in current personalization efforts is a lack of an overarching theory explaining the efficacy of individual predictors for specific populations. To overcome this main issue, Kelders (2017) proposes the development of a useful personalization approach by focusing on the underlying mechanism explaining the effectiveness of eMH interventions. If a mediator can be identified that fulfills a set of characteristics, a personalized development of digital mental health interventions may become independent of treatment and technology (Figure 1). Due to its qualities, DHI engagement may function as a mediator between ITFs and intervention effectiveness.

Figure 1

Proposed mediation model for personalization approach



Characteristic of mediator
1. *Independent predictor*: related to effectiveness of different interventions
2. *Individual*: sensitive to individual variation, so useful as individual predictor
3. *Sensitive to different ITFs*: so useful to identify optimal treatment
4. *Early measurable*: to direct each individual to the most optimal treatment
5. *Theory based*: so results can be explained and likely influential ITFs can be identified

Note. Adapted from Kelders Engagement studies (2017).

The Current Study

The need for efficient mental healthcare is high, and e-Mental health shows promising potential to address mental illnesses and to promote well-being. A specific barricade to the effective implementation of eMH is non-engagement. Although field-specific literature indicated that some form of DHI engagement can overcome this barricade and influence the effectiveness of e-Mental health interventions (Donkin & Glozier, 2012; Kelders, 2015), consistent evidence is lacking. To implement engaging e-mental health interventions, a common understanding of engagement as a multifaceted concept is essential (Kelders, van Zyl, and Ludden, 2020) and a thorough testing of pathways between engagement and intervention efficacy needs to be conducted (Short et al., 2018).

The main aim of this study was to explore the strength of the multifaceted engagement concept as a mediator in the proposed mediation model (Figure 1), and thereby provide information for a new personalization approach. Additionally, the role of intervention and technological factors was investigated. This research focused specifically on feedback variations (in text only vs in text with picture of an avatar vs in pre-recorded video of the counselor) as a predictor variable for DHI engagement and mental well-being as an outcome measure to represent intervention effectiveness. Given the importance of some kind of feedback for therapeutical interventions to be effective, it was examined whether individuals are engaged differently when support is given in different ways. In line with the given explanations, the following research questions were derived.

Research Questions

RQ1. To what extent do feedback variations (in text only vs in text with picture of an avatar vs in pre-recorded video of counselor) have a direct impact on mental well-being as an intervention effectiveness measure in a two-week e-Mental Health intervention?

RQ2. To what extent do different feedback variations (in text only vs in text with picture of an avatar vs in pre-recorded video of counselor) in a two-week e-Mental Health intervention influence DHI engagement?

RQ3. To what extent does DHI engagement mediate the relationship between feedback variations and mental well-being as the intervention effectiveness measure in a two-week e-Mental Health intervention?

Methods

Design

The study was conducted as an intervention study with a pretest-posttest design. The current study was part of a larger investigation by Kelders et al. (2017), including 27 versions of a 2-week well-being micro-intervention. The overarching research employs a 3x3x3 full factorial design consisting of three variations in intervention and technological factors (ITFs). The ITFs in the larger project are 1) the content, 2) feedback options, and 3) intervention design. In this paper, the focus was exclusively directed at variations in feedback, and their role in the proposed mediation model with DHI engagement as a mediator-, as well as an independent predictor for intervention effectiveness. Three points of engagement measurement were considered, namely on day one (T0), day three (T1), and day seven (T2). The data utilized in this paper was previously collected from October 2020 until January 2021. The study was approved by the Behavioral, Management, and Social Sciences (BMS) Ethics Committee of the University of Twente (Nr: 201118).

Participants

All of the participants were recruited through non-probability sampling. Via convenience sampling, study participants were recruited through a university intern recruitment tool (Sona Systems), a social media ad (Facebook, Instagram), or direct invitation via e-mail or LinkedIn. The remainder of the students were reached with snowball sampling by receiving recommendations from family or friends. The study included participants who were at minimum 18 years old and able to provide written, informed consent in English. Further, participants had to own a smartphone and download ‘The Incredible Intervention Machine’ (TIIM) mobile app. Also, participants had to be ‘not flourishing’ according to the Mental Health Continuum Short Form (MHC-SF) by Keyes (2009). Participants were excluded from the study if they did not meet these requirements or withdrew themselves. In the pretest, 666 participants were recorded, whereas the posttest questionnaire was filled out by 211 responders. Overall, 155 participants were found to have completed all questionnaires and met the inclusion criteria. From those 155 participants, two were removed because their personal identifier on the pretest could not be identified in the posttest. This left 153 valid participants which were assigned to the in-text only feedback condition (n=48), the in-text with picture of an avatar condition (n=57), and the pre-recorded video of a counselor condition (n=48).

Materials

TIIM mobile app. Each participant carried out one of 27 app versions via the TIIM app. Every single intervention version consisted of 14 daily modules with one exercise per day. The modules were equally structured, including a pre-and post-emotional self-assessment, an introduction to the daily exercise, the exercise itself, a feedback statement, and a closing statement. Varying between app versions, the intervention content (modules and exercises) was based on one of three existing, evidence-based interventions from therapeutic approaches, namely cognitive behavioral therapy, acceptance and commitment therapy, and positive psychology. Also, participants received one out of three possible feedback options, which were given on each exercise throughout the two-week intervention. These three feedback variations were identical in content, but displayed distinct types of representation, namely in-text only, in-text with a picture of an avatar, and a pre-recorded video of a counselor (Figure 2). In figures 3-8, the intervention introduction is illustrated as an example from an app version with positive psychology as intervention content and in-text feedback with a picture of an avatar.

Figure 2

Three feedback variations displaying in-text only, in-text with picture of an avatar, and pre-recorded video of a counselor respectively. These feedback options were taken from app versions with Meaning and Purpose as intervention content.

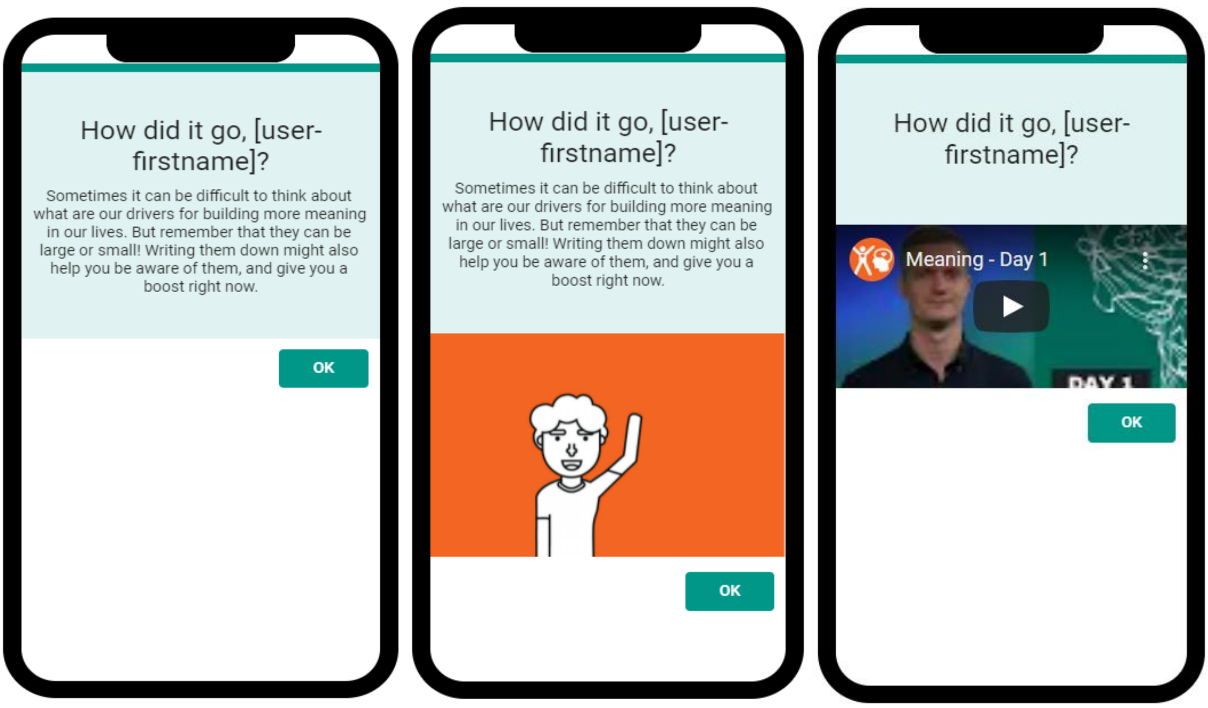


Figure 3

Welcome Screen

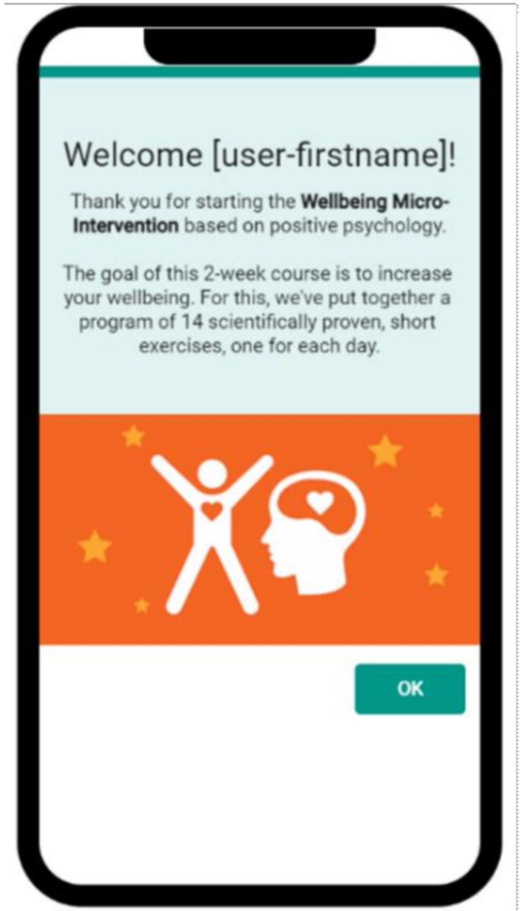


Figure 4

Intervention content

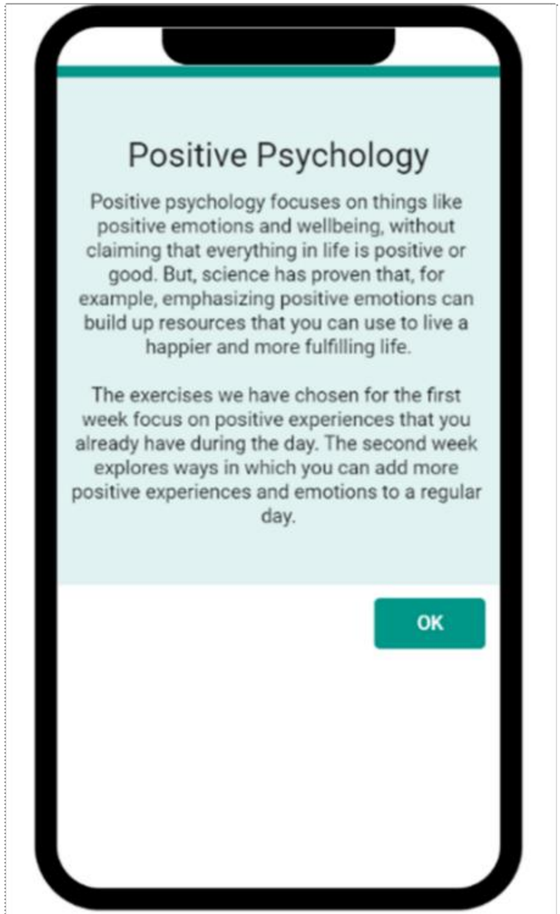


Figure 5

Intervention overview

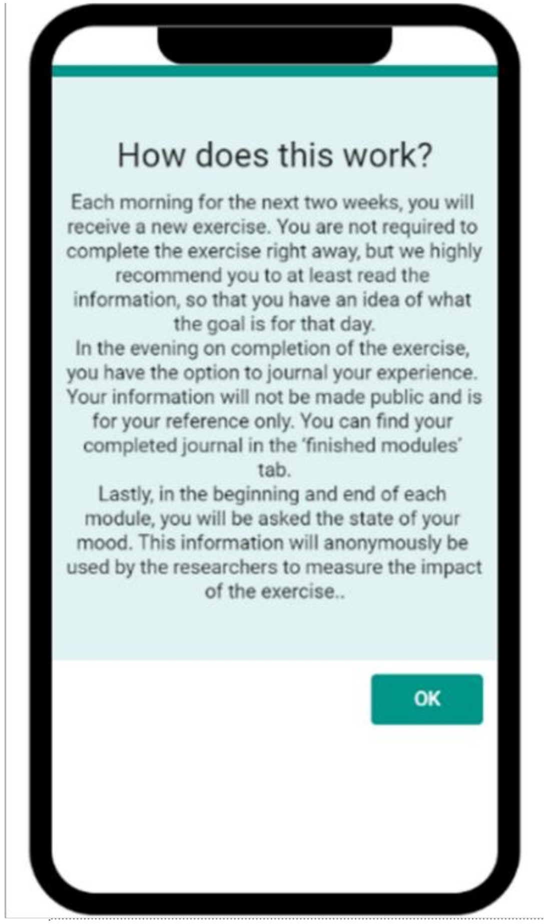


Figure 6

Formulating goals

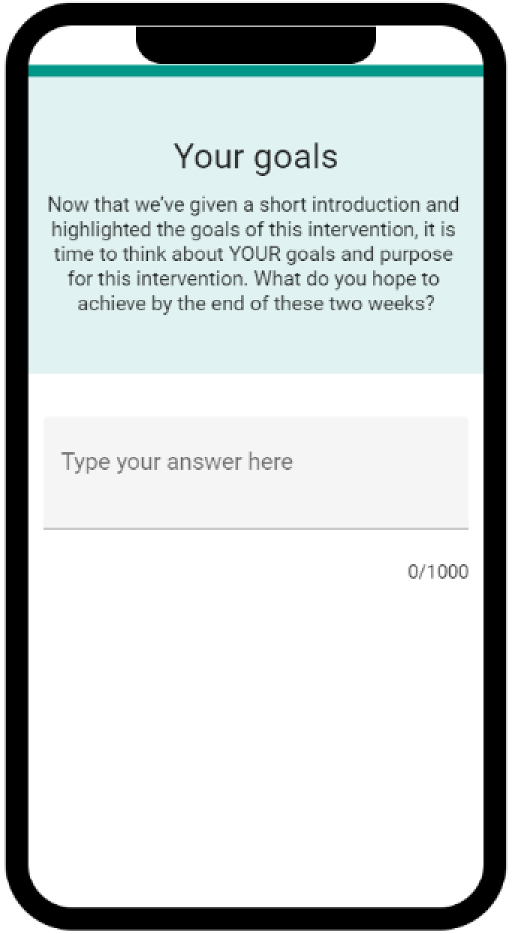


Figure 7

Avatar feedback

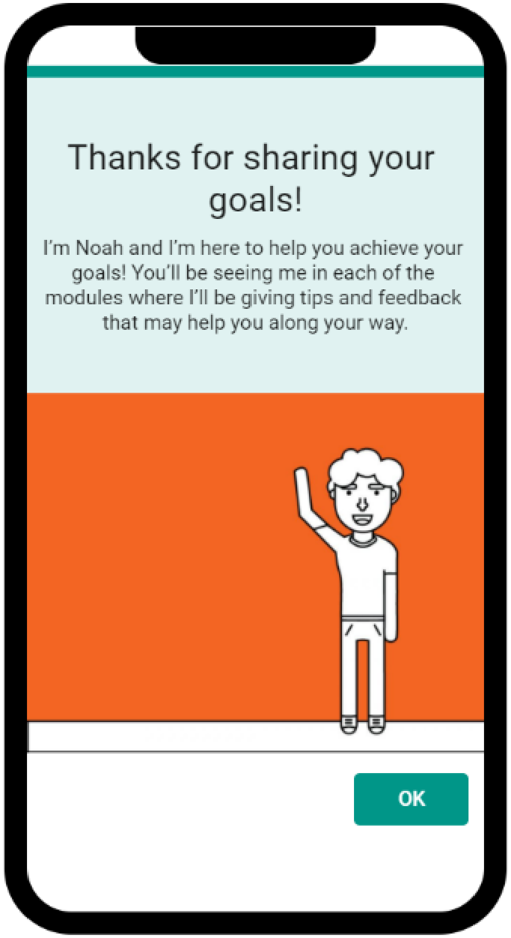
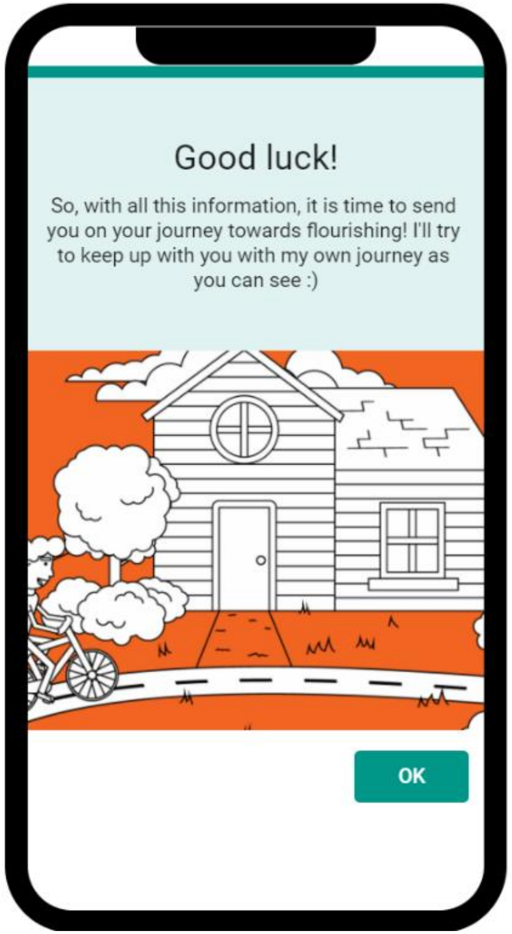


Figure 8

Good Luck!



Measures

Engagement. The TWente Engagement with Ehealth Technologies scale (TWEETS) by Kelders et al., (2020) was utilized to measure the level of user engagement at three-time points. The TWEETS consists of 9-items, covering the areas of behavioral engagement (items 1-3), cognitive engagement (items 4-6), and affective engagement (items 7-9) on a 5-point Likert scale (*strongly disagree*=0, *disagree*=1, *neutral*=2, *agree*=3, *strongly agree*=4). An example item to measure engagement with the TWEETS was: "This technology is part of my daily routine" (see Appendix A for the complete set of items). In a previous study, the scale has shown to perform well as an engagement measure with reasonable to good psychometric properties (Kelders, Kip, and Greeff, 2020). In this study, Cronbach's alpha was .81, indicating high reliability.

Effectiveness: Pre- and Post- questionnaires

MHC-SF. For the inclusion/exclusion process, the Mental Health Continuum Short Form (MHC-SF) by Keyes (2006a) was employed as a categorical diagnosis of the presence of mental health, described as flourishing, and the absence of mental health, characterized as languishing). To be diagnosed with flourishing mental health, individuals must experience '*every day*' or '*almost every day*' at least one of the three signs of hedonic well–being and at least six of the eleven signs of positive functioning during the past month. Individuals who exhibit low levels (i.e., '*never'* or '*once or twice'* during the past month) on at least one measure of hedonic well–being and low levels on at least six measures of positive functioning are diagnosed with languishing mental health. Individuals who are neither flourishing nor languishing are diagnosed with moderate mental health. For included participants, the MHC-SF was used as a continuous assessment for intervention effectiveness. The 14-item scale covers each facet of well-being, including hedonic (emotional well-being), and eudaemonic (psychological and social) that participants respond to on a 6-point Likert-scale ranging from 0 (= never) to 5 (= every day). An example item to measure emotional well-being was: "During the past month, how often did you feel…happy?" (see Appendix B for the complete set of items). In previous studies, the scale has shown good psychometric properties (Keyes, 2006a, 2006b; Keyes et al., 2008; Lamers et al., 2011; Westerhof & Keyes, 2009). In the current study, the Cronbach's alphas were $\alpha = 0.88$ at baseline and $\alpha = 0.91$ at post-test, indicating good to excellent internal reliability.

Procedure

At the sign-up, participants were provided an informed consent containing information on the research purpose, the procedure, data handling, and their (privacy) rights. To continue, the participants were required to declare their understanding and agreement with the study terms. After signing up for the study, the participants received a baseline survey (pre-test) and the information that it takes 10-15 minutes to complete. In the survey, participants were asked to indicate their e-mail address, personal identifier as well as demographic information including gender, age, employment status, nationality. Also, participants were informed that the following questions address how they are feeling through filling in the MHC-SF. Those who were not flourishing-, completed the intervention-, filled out the post-intervention survey-, and were credited 4.5 Sona credits as compensation. At the end of the baseline survey, the eligible participants were provided with links, one to enroll in the study, and a download link for the TIIM mobile app (IOS, Android). Also, participants were informed that they will be assigned to the intervention as soon as possible to start with the daily exercises which they would receive in the morning (9 a.m. local time) and be able to complete throughout the day. After the participants were assigned to one of the 27 intervention versions, they started working through daily modules for 14 consecutive days. In exceptional cases, users extended their participation to four weeks to complete the intervention. In cases of extended participation, reminders were sent to facilitate intervention completion. On the last day of participation, users filled in the post-intervention survey.

Data Analysis

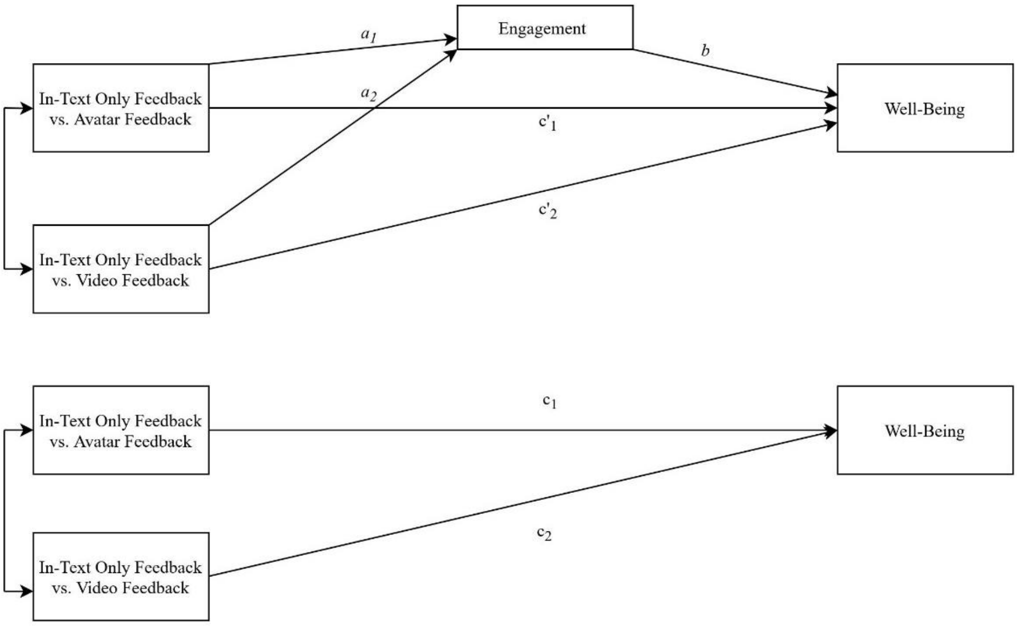
Data Analyses were performed using SPSS Statistics version 25 (IBM Corp., 2017). Throughout the statistical analyses, a *p*-value below 0.05 was assumed to be significant. As a first step to prepare analyses, the pre-and post-questionnaire data sets were merged by a personal identifier, and matched with an Excel overview of finished participants, including their TIIM code and an abbreviation for the received app version (e.g., CSA). Subsequently, TIIM datasets were filtered by engagement scores (T1-T3), which were recoded (e.g., 1 = *Strongly agree,* to 5 = *Strongly agree*). The engagement data was then merged with the pretest-posttest data set by TIIM code. The final data set was cleaned by removing participants who were not listed in the Excel overview, thus did not have an assigned TIIM code. From the remaining 153 participants, there were 68 missing responses identified on the repeated engagement questionnaires. Thereby, 19 missing responses were recorded for T1, 23 missing for T2, and 26 missing for T3. Little's MCAR test was conducted to test the hypothesis that the data were missing at random. With this assumption met, missing engagement data was imputed using the expectation-maximization (EM) algorithm (Dempster et al., 1977). After replacing the missing engagement values, psychometric properties for the TWEETS and MHC-SF were assessed. Consequently, Cronbach's alpha was used to establish the reliability coefficient.

With regard to the first research question, a two-way repeated measures ANOVA was conducted to investigate whether well-being scores differed between the three feedback variations and over time. Preliminary checks were completed to assess the assumptions of normality and sphericity. Shapiro-Wilk tests indicated normally distributed MHC-SF pretest scores for the in-text-only group $W(48) = .98$, $p = .45$, the avatar group $W(57) = .97$, $p = .09$, and the pre-recorded video condition $W(48) = .98$, $p = .69$. Posttest scores were normally distributed in the avatar group $W(57) = .99$, $p = .76$, and the video group $W(48) = .96$, $p = .11$. The Shapiro-Wilk test indicated MHC-SF posttest scores were not normally distributed in the in-text-only group $W(48) = .92$, $p = .00$. However, as the distribution was close to normal and ANOVAs are robust to this violation (Pallant, 2011), no steps were taken to address this. Time was defined as a within subject factor with two levels (pretest and posttest well-being measurement points) and feedback variation was set as a between-subjects factor with three levels (in-text-only, avatar, and pre-recorded video).

With regard to the second and third research question, serial (simple) mediation analyses were performed using the PROCESS macro tool in SPSS (Hayes, 2012). Based on the mediation models corresponding to a model with a multicategorical independent variable with *k* categories by Hayes and Preacher (2013), a simple mediation model (Figure 9) was developed. The predictor variable for the analyses was feedback variation. An indicator coding system was used to represent the multicategorical feedback variable with in-text-only feedback functioning as the reference group. The mediator variable was DHI engagement, and the dependent variable was the total mental well-being posttest score. With regard to individual changes throughout the intervention, additional simple mediation analyses were conducted with the pretest-posttest mental well-being change score as the dependent variable. Separate analyses were conducted for engagement at each time point and for both dependent variables. The *a* pathways represent the effect of the in-text with a picture of an avatar-, and pre-recorded video feedback categories relative to the in-text-only feedback condition on Engagement (T1-T3). Pathways b_1, b_2, b_3 represent the effects of DHI engagement (T1-T3) on well-being. Pathway *c* displays the relative total effect of feedback variation mean differences on well-being. The c’ paths display the relative direct effects of feedback variations on well-being after accounting for engagement T1-T3. The mediating roles were computed by calculating the indirect effects (*a* x *b*).

Figure 9

A simple mediation model in path diagram form corresponding to a model with a multicategorical independent variable with two categories.



Results

Baseline Characteristics

Table 1 displays the sociodemographic characteristics as well as the sample size for the total sample and each feedback group. The whole sample ranged in age from 18 to 64, with a relatively young average age of 21.76 (*SD* = 5.78). The majority of participants were female (73.3%), 25.5% indicated being male and 1.3% identified as diverse. Considering the distribution of ethnicity, 66% were German, 20.9% Dutch, and 12.4 % were from other countries. Regarding the employment status, the majority were students (84.3%). The feedback groups did not differ noticeably in mean age, distributions of gender, nationality, and employment status. In table 2, the mean scores of total mental well-being and engagement scores are presented. For each feedback condition, a positive mental well-being change score was found, with a greater average change score for participants from the in-text only feedback condition compared to those from the avatar- and pre-recorded video feedback conditions.

Regarding DHI engagement, the average scores dropped from T1 to T3 across feedback conditions, with the pre-recorded video condition having the greatest negative change score.

Table 1

Demographic characteristics of the participant sample and feedback variation frequency distributions (n = 153)

Variable		Total	In-Text	Avatar	Video
		n (%)	n (%)	n (%)	n (%)
Sample Size		153	48 (31.4)	57 (37.3)	48 (31.4)
Mean age	*M*	21.76	22.90	21.86	20.50
Gender	Male	39 (25.5)	14 (29.2)	14 (24.6)	11 (22.9)
	Female	112 (73.2)	34 (70.8)	42 (73.7)	36 (75.0)
	Other	2 (1.3)		1 (1.8)	1 (2.1)
Nationality	Dutch	32 (20.9)	10 (20.8)	11 (19.3)	11 (22.9)
	German	101 (66.0)	34 (70.8)	35 (61.4)	32 (66.7)
	Other	19 (12.4)	4 (8.3)	10 (17.5)	5 (10.4)
Employment status	Full-time (32-40 h)	4 (2.6)	2 (4.2)	2 (3.5)	
	Part-time (< 32 h)	4 (2.6)	1 (2.1)	1 (1.8)	2 (4.2)
	Self-employed	1 (0.7)		1 (1.8)	
	Student	129 (84.3)	38 (79.2)	48 (84.2)	43 (89.6)
	Unemployed	4 (2.6)	3 (6.3)		1 (2.1)
	Other	10 (6.5)	4 (8.3)	4 (7.0)	2 (4.2)

Table 2

Descriptives of outcome measures

	In-Text (n= 48)	Avatar (n= 57)	Video (n=48)
	M (SD)	*M (SD)*	*M (SD)*
Total Well-Being			
Baseline	46.60 (10.97)	46.30 (11.21)	47.98 (10.24)
Posttest	53.63 (11.73)	50.82 (10.55)	51.13 (10.59)
Change	7.02 (10.60)	4.53 (9.32)	3.15 (10.61)
Engagement			
T1	34.03 (3.48)	33.31 (6.15)	35.12 (3.12)
T2	33.10 (3.69)	32.28 (5.39)	32.35 (5.98)
T3	32.90 (4.25)	31.78 (6.67)	31.90 (7.87)
Change	-1.13 (4.07)	-1.53 (5.05)	-3.22 (7.96)

Intervention Effectiveness

The outcomes of the two-way repeated measures ANOVA (Table 3) showed a significant main effect of time on differences in total mental well-being scores between the pretest and posttest measurement time points for all feedback groups, Wilks' lambda = .809, $F(1, 150)=35.45$, $p < .001$. The total scores of mental well-being increased from pretest to posttest in all three feedback variation conditions, indicating evidence for intervention effectiveness. Thereby, the effect size for in-text only feedback ($d = 0.62$) was found to exceed Cohen's (1988) convention for a medium effect ($d = 0.5$), whereas effect sizes for the avatar condition ($d = 0.42$) and the pre-recorded video condition ($d = 0.30$) were found to surpass Cohen's requirements for a small effect ($d = 0.2$). However, the interaction between time and feedback variation was found to be non-significant, Wilks' lambda = .976, $F(2,150)=1.81$, $p = .17$, showing that the variation in well-being outcome scores over the repeated measurement occasions itself did not vary as a function of feedback group affiliation. This indicates that the two-week intervention was effective regardless of differences in feedback options.

The Effect of Engagement

In Table 3, the simple mediation results are displayed. Looking at the *c* paths, the results show that in-text feedback with a picture of an avatar ($B = -2.80$, $SE = 2.14$, $p=.19$) and pre-recorded video feedback ($B = -2.50$, $SE = 2.23$, $p = 0.26$) predict well-being non-significantly in a negative direction, relative to in-text only feedback, indicating a slightly higher posttest well-being score for participants from the in-text only intervention condition relative to those from the other two feedback variation groups. Analyzing the indirect effects, results reveal that engagement did not significantly mediate the relationship between feedback variation and well-being at time point one, $B = -0.49$, $SE = 0.68$, 95% CI [-1.67 to 1.15], time point two, $B= -0.41$, $SE = 0.47$, 95% CI [-1.61 to 0.47], and time point three, $B = -0.54$, $SE = 0.61$, 95% CI [-1.94 to 0.54]. Relative to in-text-only interventions, avatar and pre-recorded video conditions had a non-significant negative effect on engagement (T1-T3), except for the video condition on engagement at time point one ($B = 1.09$, $SE = 0.19$, $p = 0.13$). As expected, DHI engagement did positively predict well-being posttest scores at time point one, $B = 0.69$, $SE = 0.19$, $p < 0.01$, time point two, $B = 0.50$, $SE= 0.17$, $p < 0.01$, and time point three, $B = 0.49$, $SE = 0.13$, $p < 0.01$. Nevertheless, the results also suggest that even after accounting for the engagement (T1-T3) variable, feedback with picture of an avatar and feedback with a pre-recorded video still have a non-significant negative impact on well-being relative to the in-text-only intervention group.

In comparison, separate simple mediation analyses with the mental well-being change score as a dependent variable (Table 4) revealed similar results. Differences were that only engagement (T3) predicted the mental well-being change score from the *b* paths, $B = 0.29$, $SE = 0.13$, $p = 0.02$. The results also show a statistically significant negative relative direct effect at time point one ($B = -4.23$, $SE = 2.06$, $p = 0.04$) and a marginally significant relative total effect ($B = -3.88$, $SE = 2.07$, $p = 0.06$) of the pre-recorded video feedback condition on the mental well-being change score, relative to the in-text-only feedback condition.

In summary, no definite-, and time-independent evidence was found that differences in feedback variation predict DHI engagement, and total mental well-being. Further, engagement at all time points was found to have a positive influence on total mental well-being. DHI engagement (T3) did also have a positive influence on the mental well-being change score. Moreover, no evidence was found for a mediation effect of DHI engagement between feedback variation differences and total mental well-being, as well as pretest-posttest change scores.

Table 3

Simple mediation analyses of the effects of text vs avatar and text vs video on mental well-being (MHC-SF), mediated by DHI engagement at three time points (T1-T3)

Predictor	Mediators	*a*	*b*	Relative Total Effect *c*	Relative Direct Effect *c'*	Relative Indirect Effect *a x b* (95% CI) [a]
Text vs Avatar	Engagement T1	-0.72	0.69**	-2.80	-2.31	-0.49 (-1.67, 1.15)
	Engagement T2	-2.39	0.50*	-2.80	-2.39	-0.41 (-1.61, 0.47)
	Engagement T3	-1.11	0.49**	-2.80	-2.26	-0.54 (-1.94, 0.54)
Text vs Video	Engagement T1	1.09	0.69**	-2.50	-3.25	0.75 (-1.38, 2.40)
	Engagement T2	-2.12	0.50*	-2.50	-2.12	-0.38 (-1.29, 0.74)
	Engagement T3	-2.26	0.49**	-2.50	-2.01	-0.49 (-1.54, 0.97)

Note. [a]Bias corrected bootstrap results for the indirect effects (5,000 resamples). * $p < .05$, ** $p < .01$

Table 4

Simple mediation analyses of the effects of text vs avatar and text vs video on the mental well-being change score (MHC-SF), mediated by DHI engagement at three time points (T1-T3)

Predictor	Mediators	*a*	*b*	Relative Total Efect *c*	Relative Direct Effect *c'*	Relative Indirect Effect *a x b* (95% CI) [a]
Text vs Avatar	Engagement T1	-0.72	0.33	-2.49	-2.26	-0.23 (-0.94, 0.48)
	Engagement T2	-0.82	0.31	-2.49	-2.24	-0.25 (-1.13, 0.31)
	Engagement T3	-1.11	0.29*	-2.50	-2.17	-0.54 (-6.05, 1.71)
Text vs Video	Engagement T1	1.09	0.33	-3.88	-4.23*	0.35 (-0.08, 1.12)
	Engagement T2	-0.76	0.31	-3.88	-3.64	-0.23 (-0.93, 0.49)
	Engagement T3	-1.00	0.29*	-3.88	-3.59	-0.29 (-1.01, 0.60)

Note. [a]Bias corrected bootstrap results for the indirect effects (5,000 resamples). * $p < .05$, ** $p < .01$

Discussion

Main Findings

This study mainly aimed to examine a mediating role of DHI engagement in the relationship between feedback variation and total mental well-being as a measure for intervention effectiveness. Respectively, it was investigated to what extent feedback variations influence intervention effectiveness (RQ1) and DHI engagement (RQ2), and to what extent DHI engagement mediates the hypothesized relationship between feedback variations and total mental well-being (RQ3).

In general, the results showed a positive mental well-being development from baseline to posttest across feedback conditions, indicating that general mental well-being of a moderately mentally healthy population can be improved by a free-to-use smartphone intervention in as little as two weeks. This finding substantiates the potential of eMental health services to provide accessible quality of care, which is independent of restraints found in traditional mental healthcare such as waiting lists, costs, travel, and time (Buntrock et al., 2014). The intervention may have driven the increase in well-being by increasing awareness for the need of help, a feasible implementation into participants' everyday lives (Jeken, 2019), and providing adaptive (healthy) coping strategies such as acceptance (Prasath et al., 2021) in a variety of exercises.

Regarding the first research question, differences in provided feedback variations themselves were not found to have a significant impact on intervention effectiveness which could be explained by their similarity in features. The feedback options were equally automated, provided in the same intensity, and did not vary noticeably in content. The messages could be categorized as nonguidance contact (NGC) because they did not involve assistance in the application of the therapeutic content, but rather used cues of encouragement (Talbot, 2012). The similarities might also weaken an expected difference in delivery between text-based feedback and human support (Baumeister et al., 2014; Lehr et al., 2016). For example, the pre-recorded video condition did not offer common human-support characteristics such as the possibility for participants to interact with the counselor. Another explanation why the feedback variations did not predict intervention effectiveness could be that participants were not assigned to feedback conditions based on individual preferences. Research findings are inconclusive whether different levels of human support are different in effectiveness for the same group of participants (Baumeister et al., 2014, Linardon et al., 2019), users may thus benefit from feedback tailored to individual user needs (Li et al., 2011). However, participants of this study were not matched to feedback conditions based on specific characteristics, so this assumption could not be tested.

Regarding research question two, the feedback options did not predict DHI engagement throughout the intervention. This finding could be explained by the non-consideration of some indications and recommendations for the development of engaging eMental health interventions (Baumel et al., 2017; Achilles et al., 2020). For example, the intervention design did not include participants in the initial design process- and lacked an intermediate measure of users' expectations and preferences which could help to understand- and respond to individual user needs (Li et al., 2011). Additionally, user engagement was found to decrease from T1 to T3 which is in line with prior research (Nelson et al., 2016) and indicates that participants lost interest over time. Both findings highlight the importance for intervention designs to consider specific user needs to prevent disengagement, which is a central barricade to effective eMH services (Donkin & Glozier, 2012).

Concerning research question three, no evidence was found that DHI engagement mediates a predicted relationship between feedback variations and intervention effectiveness. This finding is unsurprising given the absence of a relationship between feedback variations and total mental well-being. To the best of the researchers' knowledge, there are currently no studies with a comparable mediation model. Nonetheless, the findings could be explained by using an incomplete theoretical concept. The initial research proposal by Kelders (2017) includes additional content- and design factors in the conceptual mediation model, such as theoretical underpinning (e.g., CBT) and levels of gamification. These excluded elements could be suppressor variables, undermining a total effect by their omission. Hence, an inclusion of these additional predictors into the mediation model could improve the predictive quality of the other variables in the initial equation (Rucker et al., 2011). Another reason for the non-significant direct and total effects in the mediation model could be due to the relatively small sample sizes in each feedback condition. With a growing sample size, the more likely become findings of significant direct- and total effects (Rucker et al., 2011).

Strengths and Limitations

One strength of this research was the comprehensive study design of the larger study. The holistic concept allowed variable research foci amongst several factors such as content, design, as well as feedback variation. Also, the data sets entail depression- and anxiety screenings. Overall, the available data provides depth and variety for further exploration, making content adjustments, and expanding the sample over time. Another strength can be considered with this research drawing on a random allocation of participants to experimental intervention conditions. The sample size and participant demographics were similar in each condition, which allowed a side-by-side comparison, by establishing equivalence between the samples in each intervention condition (Rossi et al., 2018). A final strength of this study was the confirmed influence of DHI engagement measured as a multifaceted concept on mental well-being in a digital micro-intervention for a non-clinical population, which has been sparsely explored in prior studies.

Certainly, this study also revealed some potential limitations. A methodological barrier was the concept of a personal identifier. From the outset of the study, participants were asked to independently create a personal identifier to protect their identity and match their survey entries. The code should consist of birth month and year (mmyy), the first letter of one's birthplace, and the last two numbers of one's mobile phone. For a majority of participants, pretest-deviating personal identifiers were found in the posttest, which led to matching difficulties. The process of matching pretest with posttest data required making manual corrections in a time-consuming process. Another central study limitation was found to be its limited generalizability of findings. Besides having a majority of participants being German female students, an absence of a control group, and the focus on a homogenous, moderately healthy target group suggest a cautious interpretation of findings. Here, the demographics are not representative for a general population cut and did not consider clinical populations. Regarding the latter, the quantitative eligibility criteria used for diagnoses did not include screenings for mental illnesses and individual psychological characteristics. Consequentially, a precise understanding of study participants' psychological well-being was limited which makes it difficult to formulate recommendations about what condition works best for whom.

Implications for Future Research and Practice

In comparison to this study's findings, field-specific research established the importance of some form of feedback and support for DHI engagement and intervention effectiveness (Beattie et al., 2009; Bendelin et al., 2011, Baumeister et al., 2014; Linardon et al., 2019). There are indications that nonguidance contact in forms of ongoing symptom monitoring, prompts to monitor or encourage adherence, or reminders to complete outcome measures has an impact on self-administered intervention effectiveness (Talbot, 2012). Despite these default intervention features, it is important for users of digital health interventions to receive individualized information such as personalized guidance (Peng et al., 2016), whereby personalized feedback shows to improve DHI engagement (Sharpe et al., 2017). With this potential of ITFs, such as variations in feedback to affect DHI engagement, and this study's finding that DHI engagement predicts total mental well-being, it is assumed that personalized ITFs may improve the mediation model (Figure 1). Hereby, finding a potential relationship between ITFs and intervention effectiveness could enable further testing of DHI engagement as a mediator. Based on the synthesis of field-specific research and this study's findings, developers of the TIIM application and other eMH intervention designers are thus recommended to provide personalized ITFs to DHI users.

One way to ensure this would be to initiate a co-designing mobile app process. In collaboration with users, participant feedback could be adjusted, tested, and evaluated from representative target group users instead of designing the whole system without considering its users (Burns, 2018). This approach can capture and utilize individual perceptions, as well as preferences, which facilitates DHI acceptability and engagement (Patel et al., 2020; Alqahtani et al., 2021). Besides a collaborative design process, intervention allocation can be improved by tailoring intervention content to psychological characteristics (Dugas et al., 2020), and help to examine optimal levels of contact for a set of participant characteristics. This approach could be enabled by an assessment of the measurement instrument subscales. With regard to the MHC-SF scale, people with lower levels of self-efficacy reflected by environmental mastery and autonomy scores, or higher need for positive relations may respond less well to self-administered digital well-being interventions, or demand higher intensity guidance (Talbot, 2012).

Finally, it is suggested to provide user-matching interactive elements during the intervention to overcome decreasing DHI engagement and benefit intervention effectiveness. One approach to enhance user engagement would be to consider the TWeets subscales. For example, a female participant is found to have low cognitive and affective engagement due to finding that the app does not allow setting personal goals. Yet, her behavioral engagement remains high because she is aware of being part of a study. The implementation of individual analyses during the intervention could help to detect related response patterns, help participants to reflect on their individual progress, and make adjustments to their goal setting (Li et al., 2011). Another approach to promote DHI engagement would be to provide customizable design characteristics. For example, the frequency of reminders and push notifications should be adjustable. If that is not the case, users may just ignore them (Peng et al., 2016) and engagement could be impaired.

Conclusion

The current study found that DHI engagement measured as a multifaceted concept serves as an individual predictor for total well-being in a non-clinical population sample consisting of majorly young female college students. A mediating role of DHI engagement on the predicted relationship between feedback variation differences and intervention effectiveness was not revealed, as there was no evidence for a relationship between feedback variations and mental well-being. A plausible reason for the absence of a relationship may be the similarity of feedback conditions and neglect of individual user preferences. Based on the potential of DHI engagement to individually predict mental well-being, future research is encouraged to consider individual user demands for eMH intervention development and during its execution. With a personalization of ITFs, the strength of engagement as a mediator should be re-tested to advance eMH personalization efforts.

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Appendices

Appendix A

The Twente Engagement with Ehealth Technologies Scale (TWEETS)

Item	Thinking about using [the technology] the last week, I feel that:	Construct
1	[this technology] is part of my daily routine	Behavior
2	[this technology] is easy to use[a]	Behavior
3	I'm able to use [this technology] as often as needed (to achieve my goals)	Behavior
4	[this technology] makes it easier for me to work on [my goal]	Cognition
5	[this technology] motivates me to [reach my goal]	Cognition
6	[this technology] helps me to get more insight into [my behavior relating to the goal]	Cognition
7	I enjoy using [this technology]	Affect
8	I enjoy seeing the progress I make in [this technology]	Affect
9	[This technology] fits me as a person	Affect

[a]Based on the outcomes of this study, this item was later changed to "[this technology] takes me little effort to use."

Appendix B

The Mental Health Continuum Short Form (MHC-SF)

During the past month, how often did you feel…	NEVER	ONCE OR TWICE	ABOUT ONCE A WEEK	2 OR 3 TIMES A WEEK	ALMOST EVERY DAY	EVERY DAY
1. happy						
2. interested in life						
3. satisfied with life						
4. that you had something important to contribute to society						
5. that you belonged to a community (like a social group, school, neighborhood, etc.)						
6. that our society is a good place, or is becoming a better place, for all people						
7. that people are basically good						
8. that the way our society works made sense to you						
9. that you liked most parts of your personality						
10. good at managing the responsibilities of your daily life						
11. that you had warm and trusting relationships with others						
12. that you had experiences that challenged you to grow and become a better person						
13. confident to think or express your own ideas and opinions						
14. that your life has a sense of direction or meaning to it						

Appendix C

List of Interventions varying in content, feedback, and design

Intervention	feedback
Flourishing PNA – Positive Psychology	Avatar
PNV – Positive Psychology	Video
PNT	Text only
MNV – Meaning and Purpose	Video
MNT – Meaning and Purpose	Text only
CNV – CBT	Video
CNT – CBT	Text only
Flourishing CSV – CBT2	Video
PNA – Positive Psychology	Avatar
MNA – Meaning and Purpose	Avatar
CNA – Cognitive Behavioral Therapy	Avatar
PCV – Positive Psychology	Video
MCV – Meaning and Purpose	Video
CCV – Cognitive Behavioral Therapy	Video
MCT – Meaning and Purpose	Text only
PCT – Positive Psychology	Text only
CCT – Cognitive Behavioral Therapy	Text only
PCA – Positive Psychology	Avatar
MCA – Meaning and Purpose	Avatar
CCA – Cognitive Behavioral Therapy	Avatar
PSV – Positive Psychology	Video
MSV – Meaning and Purpose	Video
CSV – Cognitive Behavioral Therapy	Video
PST – Positive Psychology	Text-only
MST – Meaning and Purpose	Text-only
CST- Cognitive Behavioral Therapy	Text-only
MSA – Meaning and Purpose	Avatar
CSA – Cognitive Behavioral Therapy	Avatar
PSA – Positive Psychology	Avatar