The Best Possible Self Intervention: The mediating effect of engagement with technology between the BPS future and past intervention and well-being

M.Sc. Thesis

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Abstract

Background. While the Best Possible Self (BPS) intervention has shown to be effective to increase well-being in prior research, the underlying mechanisms responsible for those effects are not fully discovered yet. (Sheldon & Lyubomirsky, 2006). Therefore, as the intervention was delivered using a mobile application, it is of interest to explore whether levels of user engagement can influence the effects of the BPS. Further, while the role of temporality, namely whether focusing on the past can produce similar results as focusing on the future, is not determined yet, it will be investigated whether the temporality might affect user engagement. Thus, this study aims to explore (1) whether levels of user engagement differ over time, (2) between time conditions and (3) whether user engagement had a mediating effect on well-being.

Methods. This study was a randomized controlled trial (RCT) with three conditions: past and future (n = 100), future (n = 95) and control (n = 95). A guided mobile application was used as a delivery method for the intervention. Participants were instructed to write about their best possible self in the future (future condition), about their past best self during the first week of the intervention and their best possible self in the future during the second week (past/future condition), and about activities, they carried out during the last 24 hours (control condition). The main outcome measures were well-being and levels of user engagement at different time points (before, during and after the intervention).

Results. The RM-ANOVA showed that levels of user engagement decreased over the two weeks but did not differ between the past, future and control condition. Further, no significant differences between the subdimensions of user engagement could be detected. PROCESS mediation analysis revealed that user engagement was not a mediator between condition and well-being, but that the amount of engagement did predict well-being in all three conditions.

Conclusion. This study revealed that user engagement had an impact on the outcomes of the BPS intervention, even though it did not act as a mediator between condition and well-being. This can be explained by the fact, that temporality was not found to be essential for the BPS intervention to be effective, and thus no differences in the conditions could be detected. Further, that user engagement and its subdimensions decreased over time during the study supports the view that strategies to enhance cognitive, behavioural and affective engagement should be explored in future research.

Keywords: Best-Possible-Self-Intervention, levels of user engagement, past/future BPS

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The Best Possible Self Intervention: The mediating effect of engagement with technology between the BPS future and past intervention and well-being

In today`s society, more and more people from all over the world experience stress and suffer from mental health problems, which underlines the importance to investigate how the mental health of people can be enhanced effectively. Mental health was long purely defined as the absence of mental illness, but nowadays, mental health can rather be characterized as a state of well-being in which people can reach their full potential by actualising their own abilities and strengths while experiencing positive emotions (WHO, 2005). In line with that, research has confirmed that well-being is associated with many positive outcomes, such as better relationships, better health and more satisfaction in life (Winefield, Gill, Taylor & Pilkington, 2012). Thus, studying ways to increase well-being and hence, the mental health of individuals, is very relevant in our fast-paced world. In accordance with that, the approach of positive psychology puts the focus on this issue, by investigating what enables individuals to thrive and to build a life of purpose and meaning (Seligman, 2004).

Emerging from the movement of positive psychology, so-called “Positive psychology interventions” (PPI´s) are scientific tools that aim to promote well-being, happiness and positive emotions (Keyes, Fredrickson & Park, 2012). Topics that are addressed through PPI´s are, for example, gratitude, optimism or empathy and interventions entail imaginary exercises, diary tasks or mindfulness practices to broaden attention for positive emotions (Carr et al., 2020). Furthermore, it has been found, that PPI´s complement instead of replace more traditional psychological interventions by focusing on increasing well-being rather than reducing psychopathology. Moreover, research has shown that the focus on positive emotions also resulted in a lower recurrence of symptoms and in sustained positive long-term effects (Lamers, Bolier, Westerhof, Smit & Bohlmeijer, 2012).

The best possible self

One example of a PPI that showed to be effective to increase well-being is the best possible self (BPS) intervention which was first developed by Laura King (2001). The BPS asks participants to think about and write down themselves in their best possible future in which they achieved everything they desired (Sheldon, & Lyubomirsky, 2006). That the intervention is effective to increase well-being can be explained by means of different theories. For example, the broaden-and-build theory states that positive emotions can result in broadening people’s awareness and attention, which in turn serves to build their physical, psychological and social resources (Fredrickson, 2001). Applying the theory to the BPS intervention shows, that people might be more aware of their positive emotions by imagining their best possible selves, which could lead to more resources to resolve conflicts and to reach goals (Liau, Neihart, Teo & Lo, 2016). This, in turn, could then result in a higher level of well-being, which was confirmed in different studies in the past. For example, Peters, Meevissen and Hanssen (2013) found out, that well-being and optimism were increased in participants who took part in a two-week BPS intervention compared to a control group.

While the BPS can be described as a future-oriented intervention, which makes use of the role of future imagination through asking about the best possible future, it is rarely researched whether the future as a time frame is indispensable for the PPI to be effective or if focusing on the past or present can lead to similar effects on well-being (Carillo, Etchemendy & Baños, 2020). In their study, Carillo et al. (2020) found out that writing about one´s past, present and future best-self led to similar results with regard to an enhancement of well-being. However, no statistical difference could be found when comparing the experimental and control group, which means that the results are not conclusive yet. Thus, there is a need to further investigate whether the temporal focus is essential for the efficacy of the BPS intervention, or if other processes might have more influence on the outcome. Understanding why PPI´s such as the BPS result in higher well-being is essential in order to use them most effectively. Even though the mechanisms underlying the effectiveness of the BPS are not fully discovered yet, some studies have already been conducted to assess the efficacy of the exercise in different contexts and procedures. For example, a meta-analysis by Loveday, Lovell and Jones (2018), which compared the effects of over 30 studies, showed that the BPS intervention has been effective to increase well-being in different samples (clinical and non-clinical) as well as when the exercise was delivered in-person or online.

With regard to online interventions, there is a trend towards making use of technology and the internet to support and improve psychological treatment. So-called Online Positive Psychology Interventions (OPPI´s), for example, applications on mobile devices, can “engage and empower participants to take charge of their own health and well-being” (Bolier & Abello, 2014, p. 289). Moreover, those internet-based interventions bring the benefit that broader populations can be reached and that they are often more cost-effective compared to in-person interventions, as the interventions can be delivered at lower costs (Baños, Etchemendy, Mira, Riva, Gaggioli & Botella, 2017). Several studies have confirmed, that no differences in outcome variables could be found when administering the BPS intervention online versus in-person (Enrique, Bretón-López, Molinari, Baños & Botella, 2018; Layous, Nelson & Lyubomirsky, 2013) and that the online format is nowadays even considered as the standard delivery method when using the BPS exercise (Ng, 2016).

Engagement with technology

One aspect that needs to be considered when conducting a study that makes use of OPPI´s, is the amount of user engagement with the application, as a higher level of engagement with the technological intervention might be associated with an increased level of behavioural change (Bender, 2014). During the last decade, the conceptual difference between adherence and engagement has been elaborated. While adherence to the technology only covers the objective usage of technology, including temporal patterns such as frequency or duration of app usage and demonstrates whether the application was used as intended, the concept of user engagement goes beyond that point (Bender, 2014). For example, a review by Perski et al. (2016) has conceptualised user engagement as a subjective experience characterized by attention, interest and affection. In earlier research, engagement was often only seen in behavioural terms, namely the usage of a technology, which would nowadays refer to adherence.

Kelders, Van Zyl and Ludden (2020) revealed that user engagement encompasses affective, behavioural and cognitive components and that it entails how involved or occupied someone is with the technology. According to Kelders et al. (2020), cognitive engagement includes the users' beliefs that the technology can motivate and benefit them to reach their goals and can enhance their ability to do so. In line with that, users who are cognitively engaged with the technology might be more inclined to show mental effort when using the technology. Further, the part of affective engagement covers that the participants experience and perceive positive emotions when using the technology and whether the users can identify with the technology and feel connected to it (Kelders et al., 2020). Finally, the behavioural dimension entails whether participants are able to have a routine in using the technology and can integrate it into their daily life. Thus, according to Kelders et al. (2020), the behavioural part of engagement rather focuses on the quality of the behaviour instead of only the objective usage frequency, which underlines the differences between user engagement and adherence again.

It is worth mentioning that Kelders et al. (2020) have found that the dimensions may not be equally distributed for each individual, as every individual possesses their own engagement style. However, the three dimensions can complement and support each other to enhance the individual level of engagement effectively. For example, when the behavioural component is less present in one individual, namely that a person perceives difficulties to keep a routine with the technology, a high amount of affective engagement can work against that. For example, by acknowledging the personal relevance of the technology and the positive emotions that come with it, which might result in high user engagement. Based on those findings, Kelders et al. (2020) conclude that “it seems important for eHealth technology to allow and design for different forms of engagement to make sure users will not be dependent on one form or shape of engagement that does not fit their own engagement style” (p. 6). Hence, to grasp an understanding of user engagement and its effects on psychological technologies, it is important to look deeper into the dimensions of engagement.

In general, user engagement often holds as a precondition for the effectiveness of an intervention, especially when the interventions aim to change behaviour (Yardley et al., 2016). While digital interventions showed to deliver health information and were successful in improving health outcomes, such as the BPS intervention, the strength of the effect is often inhibited by low user engagement as well as high drop-out rates (Alkhaldi, Hamilton, Lau, Webster, Michie & Murray, 2015). Factors that influence the amount of user engagement with the technology are for example the product design and the amount of human contact in that study (Baumel & Kane, 2018). In addition, the length of a study has shown to influence user engagement, as longer web-delivered interventions have reported lower rates of user engagement (Nelson, Coston, Cherrington & Osborn,2016). In line with that, several studies have also confirmed that user engagement decreased over the course of online interventions (Connelly, Kirk, Masthoff & MacRury, 2013; Cotter, Durant, Agne & Cherrington, 2014; Nelson, Coston, Cherrington & Osborn, 2016). Furthermore, it was also found that the engagement with the technology is affected by the “ability of the system to challenge individuals at levels appropriate to their knowledge and skills” (O'Brien & Toms, 2008, p. 939). Indicating that the level of difficulty of a task might influence their engagement behaviour. This occurrence can be explained by the fact that an appropriate amount of challenge can affect the intrinsic motivation of users and thus their willingness to engage with the technology (O'Brien & Toms, 2008).

As user engagement can have such an influence on the study outcomes, Layous et al. (2016) have recommended that future technology-based studies should take user engagement into account and examine possible associations between user engagement and the outcome variables. Only when considering the amount of user engagement and its underlying dimensions, valid conclusions can be drawn about the study outcomes of a mobile-based intervention (Yardley et al., 2016). Especially when comparing different contexts, for example, the time frame of the past and the future of the BPS intervention, it is essential to investigate in an explorative way whether the user engagement and its dimensions differed between those conditions. Even though no prior research focused on possible differences in user engagement with temporal orientations, it might be possible that those differences exist, as participants could perceive it as more difficult to imagine the future self or the past self, which could influence how much they engage with the technology. For example, some participants could find it easier to focus on the future, as they might have experienced traumatic situations in the past and do not feel comfortable with focusing on the past (Carillo, 2020). The time frame could then affect whether the participant perceives positive emotions when using the app, and thus whether the participant is affectively engaged with the application. On the other hand, someone, who is afraid of what the future might bring, could find it easier to write about the best past self and thus possesses higher levels of user engagement for this time frame (Carillo, 2020). To conclude, it could be possible that user engagement and its dimensions might differ between the time frame conditions due to individual preferences and their effect on the perceived level of difficulty. However, current research on the effects of a BPS intervention on well-being did not put the focus on user engagement and its dimensions when analysing the effectiveness of the PPI, indicating that the actual influence of the user engagement with regard to the BPS intervention is not fully discovered yet.

This study

To summarize, while a relationship between the best possible self-intervention and well-being has been confirmed in different studies (Carillo, Etchemendy & Baños, 2020; Loveday, Lovell & Jones, 2018), more research is needed to discover whether user engagement can influence this relationship and whether differences between the levels of user engagement can be detected. Furthermore, as only a few studies have started to also focus on the past self when applying the BPS within research, the levels of user engagement should also be compared for the different conditions. Hence, this research makes use of three different conditions (past/future, future and control) to test for differences in the levels of user engagement between those conditions: Each condition lasts for two weeks but while the future condition consists of writing about the best possible self for two weeks, the past/future condition entails visualizing and writing about the best past self for a week and then switches to imaging and writing down the best possible self for the future in the second week. In the control condition, participants are asked to document the activities they did in the last 24 hours for a two week-period. This study aims to explore whether the levels of user engagement differed between the past, future and control condition and over time. Further, it will be investigated whether user engagement can influence the effects of the BPS past and future intervention on well-being. Consequently, this research will answer the following research questions:

(1) What are the differences in levels of user engagement between the past, future and control condition?
(2) What are the differences in levels of user engagement over time?
(3) To what extend can user engagement mediate the effects of the BPS past and future intervention on wellbeing?

Methods

Participants

Participants in this study were recruited through an online advertisement on Facebook. At first, 745 signed up for the study and were tested for eligibility. To be eligible for participation, the following inclusion criteria were determined: Participants (a) were 18 years or older, (b) possessed a smartphone with an internet connection, (c) had an email address, (d) had sufficient Dutch skills; (e) reported low to moderate levels of well-being, as measured by the MHC-SF (Lamers, Westerhof, Bohlmeijer, ten Klooster & Keyes, 2011); (f) did not have a high level of depressive symptoms, determined by a cut-off score >33 on the CES-D scale (Radloff, 1977); (g) showed low to moderate levels of anxiety, measured by a score >15 on the GAD-7 scale, and (h) provided informed consent. After that, the remaining 563 participants were invited to fill out the baseline assessment. In this step, 204 participants dropped out of the study as they either did not respond, did not download the app or had an incomplete baseline assessment. The remaining 395 participants were then randomly assigned to either the control group, the past/future group or the future group. Participants who did not open the app after being assigned to a group were excluded from the study as well, leading to the fact that the final analysed sample consisted of 290 participants (control group n = 95; past/future group n = 100; future group n = 95). A more detailed illustration of the participants` selection and exclusion criteria can be seen in Figure 1 below.

With regard to the characteristics of the participants, the majority of the participants were Female and Dutch in all three groups. The age of the participants ranged from 19 to 72 in the full cohort. Moreover, nearly half of the participants reported HBO as their highest educational level and 2/3 of the participants were full-time employed. The exact values of the demographic characteristics of the three groups separately as well as of the full cohort are reported in Table 1. The randomisation process was successful as no differences in the demographics between participants in the three groups were detected. In Table 1, the reported p-values of the Chi-square test for the categorical variables and the p-values of the ANOVA for age can be seen.

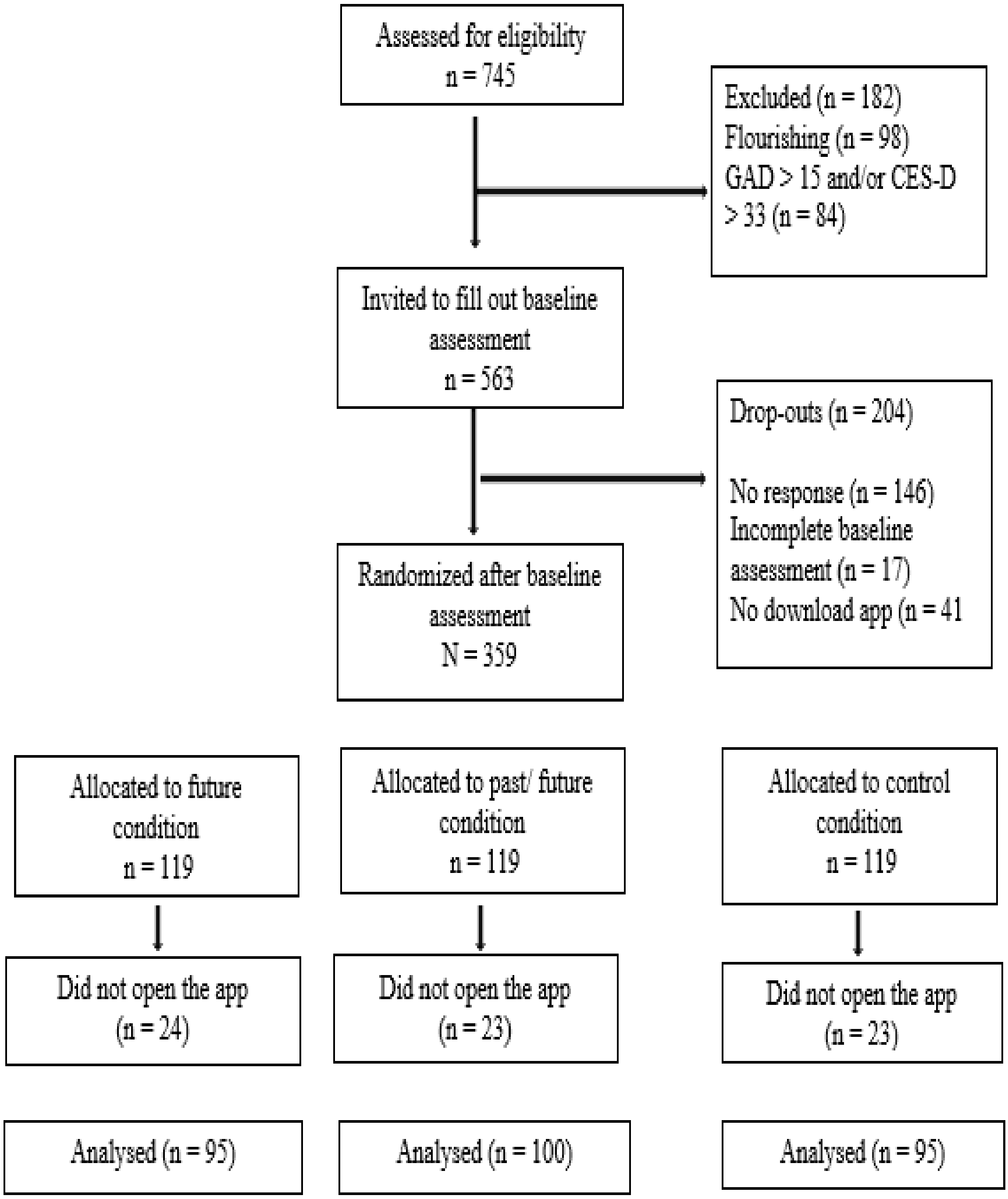


Figure 1. Flowchart of participant selection procedure

Table 1

Demographic characteristics of participants (N = 290)

Baseline Characteristics

	Condition								
	Past		Future		Control		Total		Chi-square Sig.
	N	%	N	%	N	%	N	%	
Gender									.50
Female	94	94	85	89.5	88	92.5	267	92.1	
Male	6	6	10	10.5	7	7.4	28	7.9	
Nationality									.39
Dutch	99	99	95	100	95	100	289	99.7	
Others	1	1	0	0	0	0	1	1	
Education									.95
High education (University)	26	26	23	24.2	21	22.1	70	24.1	
Moderate education (HBO, HAVO, VMBO, etc.)	72	72	70	73.7	71	74.8	213	73.4	
Low education (LBO)	1	1	1	1	1	1	3	1.03	
Occupation									.16
Full-time employed	58	58	66	69.5	69	72.7	193	66.6	
Self-employed	10	10	14	14.7	15	15.8	39	13.4	
Unemployed	15	15	10	10.6	3	3.2	28	9.7	
Others (student, volunteer, retired)	17	17	5	5.4	8	8.4	30	10.3	
Marital status									.51
Married	41	41	47	49.5	47	49.5	135	46.6	
Divorced	20	20	16	16.8	21	22.1	57	19.7	
Unmarried	38	38	29	30.5	26	27.4	93	32.1	
Widowed	1	1	3	3.2	1	1	10	1.6	

Living situation									.33
Living together with partner and children	29	29	35	36.8	30	31.6	94	32.4	
Living together with partner	29	29	21	22.1	29	30.5	79	27.2	
Single household	25	25	28	29.5	17	17.9	70	24.1	
Alone with children	13	13	10	10.5	18	18.9	41	14.1	
Others (with parents/others)	4	4	1	13.5	1	1.1	6	2.2	
	M	SD	M	SD	M	SD	M	SD	ANOVA Sig.
Age	46.09	10.82	46.91	9.92	47.36	10.18	46.78	10.3	.67

*Note. * p < .05*

Materials

Screening. As a high level of well-being, anxiety or depression was chosen as an exclusion criterion for this study, those constructs were measured during the screening procedure. The GAD-7 scale was used to measure the anxiety level of the potential participants. The questionnaire consists of 7 items and has been widely used in different kind of studies to report a general level of anxiety (Alghadir, Manzar, Anwer, Albougami, & Salahuddin, 2020). An example of an item would be "*worrying too much about different things".* Each item of the scale can be scored between 0 (not at all) and 3 (every day). The total score indicates a mild, moderate or severe level of anxiety and in this study, a cut-off score of > 15 indicating severe anxiety was used as exclusion criteria. Psychometric properties of the questionnaires can be considered as very good, as the scale showed to have high internal consistency, with a Cronbach´s alpha ranging in most studies from .83 to .93 (Johnson, Ulvenes, Øktedalen & Hoffart, 2019). Similar to those results, a Cronbach´s alpha of .76 was found in this study which can be considered as very good as well.

To screen the participants for depression, the CES-D scale was chosen. The questionnaire consists of 20 items and covers the symptoms of depression and assesses the frequency of symptoms during the last week (Radloff, 1977). The scale follows a 0-3 Likert scale ("rarely or none of the time" to "most of all of the time") with a score range of 0-60. In this study, a total score of >33 was chosen as a cut-off score for exclusion. An example of an item is "*I was bothered by things that usually don't bother me*". The questionnaire showed to have very good psychometric properties as several studies have confirmed high internal consistency. For example, a study by Siddaway, Wood and Taylor (2017) reported a high internal consistency in different samples (ɑ = .85 to ɑ = .90). In this study, a Cronbach´s ɑ of .81 has been found, which can also be considered as high.

Screening and primary outcome. Finally, the Mental Health Continuum-Short Form (MHC-SF) questionnaire was used to measure well-being during the screening procedure as well as during the actual study (Lamers et al., 2011). The questionnaire comprises 14 items and covers the dimensions of emotional well-being, social well-being and psychological well-being. Participants had to answer the questions on a 6-point Likert scale (1= never to 6= every day) and were asked to rate the frequency of every feeling in the past month. An example of an item would be *"In the past month, how often did you feel interested in life*?" Total scores range from 14 to 84 and participants whose scores were interpreted as "flourishing" were excluded from this study beforehand. As the MHC-SF was also used as a measurement instrument for the actual study, participants from all conditions had to fill in the questionnaire at baseline (T0), as an intermediate assessment after 1 week (T1), as a past assessment after 2 weeks (T2) and as a follow-up, 4 weeks after the study (T3). With regard to the psychometric properties of the MHC-SF, several studies reported high internal consistency (ɑ = .89) (Lamers et al., 2011). In this study, Cronbach´s alpha was calculated for each measurement time and showed to be high during all measurement moments (T0 ɑ = .83, T1 ɑ = .9, T2 ɑ = .91, T3 ɑ = .92).

Primary outcome. Besides the MHC-SF measuring well-being, the Twente Engagement with Ehealth Technologies Scale (TWEETS) was used in this study to assess the level of engagement with the technology, in order to answer the research questions. The questionnaire consists of 9 items on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree) and covers the dimensions of behavioural engagement, cognitive engagement and affective engagement (Kelders, Kip, Greeff, 2020). Total scores range from 5 to 45. An example of an item is "*I think using the app can become part of my daily routine*". In this study, participants had to answer the TWEETS as an intermediate assessment after 1 week (T1) and as a past assessment after 2 weeks (T2). Psychometric properties of the scale can be considered as very good as a study by Kelders, Kip and Greeff (2020) reported Cronbach alpha values of .86 and .87 showing a high internal consistency in different measurement time periods. Moreover, reasonable test-retest reliability and convergent validity were also found in the study of Kelders, Kip and Greeff (2020). In the current study, a Cronbach´s alpha of .88 was found at the T1 measurement and a Cronbach´s alpha of .93 at the T2 measurement, indicating an excellent internal consistency.

Intervention

At the beginning of the intervention, all participants were introduced to the virtual guide of the participants who was called “Dan”. In Figure 2, an illustration of Dan can be found. He informed the participants that he would teach them how to make use of their power of imagination to increase their well-being. The participants also received the information, that the training would last for two weeks and would consist of daily imagination practices that take about five to ten minutes. Then, Dan introduced a practice exercise in which participants had to imagine a lemon and their feeling when taking a bite from a lemon. After that, Dan introduced the imagination exercise which differed for each condition. However, every exercise of each condition, begun with asking participants to find a quiet place where they would not be distracted, to sit straight, close their eyes and observe their breathing. Furthermore, to encourage that participants would adhere and engage with the application, Dan reminded the participants on different occasions that a wandering mind is normal during the exercise and that keeping up with the practice would make the task easier. Furthermore, the participants also received compliments from Dan when they completed the imagination exercise and were informed about the progress of the training.

Figure 2. Illustration of the virtual guide of the intervention

Best Possible Self (BPS). The BPS condition entails imaging oneself in the best possible future in which they achieved everything they desired (King, 2001; Meevissen et al. 2011). During the training, participants were asked to imagine and write down their best possible self in the following domains: personal strengths, social relationships, professional achievements and during leisure time. The different domains were chosen to ensure that participants did not have to complete the same exercise over the period of two weeks and were based on previous research (Meevissen et al., 2011).

Best Past Self/Best Possible Self (BPAS/BPS). In the first week of this condition, participants were asked to visualize and write down a moment in the past when they showed the best version of themselves, including the goals they had accomplished and the features and characteristics they possessed at that moment (Carillo et al., 2020). After a week, the focus switched from the past to the future self. Participants were instructed to imagine and write down their best possible self after everything has gone as they desired. The same variances in exercises as in the BPS condition were used for both weeks.

Control condition. Participants who were allocated to the control group had to remember and write down the activities they did during the last 24 hours (Carillo et al., 2020; Enrique et al., 2017; Meevissen et al. 2011, Sheldon and Lyubomirsky, 2006). To ensure that participants did not have to complete the same exercises each day, they were instructed to focus on activities they did at different time points (morning, afternoon or evening).

Study design

The study design was a four-wave randomized controlled trial with three conditions: (1) the Best Possible Self (BPS), (2) the Best Past Self and Best Possible Self (BPAS/BPS) and a (3) control condition. Participants filled out questionnaires at baseline (T0), one week after the start of the study as intermediate assessment (T1), at post-assessment at the end of the intervention (T2), and at a four-week follow up (T3). This research was approved by the Faculty of Behavioural Sciences Ethics Committee at the University of Twente and given the registration number BCE16337. The research was registered in the United States National Institute of Health Registration System (NCT03024853) and the mobile application "TIIM" was used as delivery method.

Procedure

In this study, advertisements on Facebook were used to recruit participants from the general population. The following advertisement message was used for recruitment to ensure, that people who seek well-being were inclined to take part in the study: *"Do you want to grow your confidence? Soon we will start with a study in which you will boost your confidence, happiness and satisfaction with life through exercises presented on a mobile application for a two-week period"*. The message also included a link to the research web page on which people received more information about the study purpose and were able to sign up for the research by filling out an online questionnaire for screening purposes.

When the participants met the inclusion criteria for the study, they received an invitation mail to start the study and a link to the first online questionnaire by means of a baseline assessment. If participants filled out the questionnaire, they received information on how to download the mobile application. After that, all participants who installed the app were randomly assigned to the BPS condition, BPAS/BPS condition or control condition. For this, the random sequences generator on www.random.org was used to guarantee that each participant had an equal chance of being assigned to the different conditions. Finally, to minimize the drop-out rates of this study, several strategies were applied: First of all, all participants received email reminders to complete the questionnaires. Furthermore, one gift card worth 100 euros, five gift cards worth 50 euros and 20 gift cards worth 10 euros for an online store were giving away among participants who completed all assessments.

Data analysis

Statistical analyses were performed using the statistical program for social sciences (SPSS, version 24). Prior to statistical analysis, missing values were imputed in SPSS to prepare the data and account for missing values.

Descriptive statistics. With regard to the variables ``engagement with technology" and "well-being", frequency tables were created to provide an overview of the TWEETS and MHC-SF total mean scores and standard deviations (SD´s) for all 3 groups in the different measurement periods (T0, T1, T2 & T3). Furthermore, the scores of the dimensions behavioural, cognitive and affective engagement were created for the measurement time points T1 and T2 among all three conditions.

Inferential statistics. With regard to the first and second research question, a 3x4 repeated-measures ANOVA was performed to test whether the levels of engagement differed between the three conditions and over time. The different measurement time points (T1& T2) were defined as within-subject variables and the three conditions (control, past/future & future) as between-subject variables. To differentiate between the levels of user engagement, 3x4 repeated measures ANOVA was performed for each dimension of engagement, as well as for the total score of user engagement, separately.

With regard to the third research question, at first, a 3x4 repeated-measures ANOVA was conducted to detect whether well-being differed between the three conditions and between the different measurement time points. The different measurement time points (T0, T1, T2 & T3) were defined as within-subject variables and the three conditions (control, past/future & future) as between-subject variables. A p-value $<.05$ would indicate statistical significance. If a statistical significance was found, a Bonferroni adjustment post-hoc analysis would be conducted to receive more information on the differences.

After that, a simple mediation analysis was conducted using PROCESS macro for SPSS by Hayes (2017) to investigate the mediating role of user engagement on the relationship between condition and well-being. In total, two mediation analyses were performed: One with user engagement at T1 as mediator, well-being at T2 as dependent variable and condition as independent variable (´BPS-past = 1´and BPS-future = 0´) and another with user engagement at T2 as mediator, well-being at T3 as dependent variable and condition as independent variable (´BPS-past = 1´and BPS-future = 0´). The nonparametric bootstrapping method was used to investigate the mediating role of user engagement as it showed to have high statistical power and accuracy (Hayes, 2017). With regard to the interpretation of the results, a mediation effect is significant if the 95% bootstrapped confidence intervals do not comprise zero.

Results

Descriptive statistics

Well-being and User engagement. In Table 2 an overview of the total means (M) and standard deviations (SD) of well-being and the levels of user engagement (total scores and subdimensions) at the different measurement time points among the three conditions can be found.

Table 2

Descriptives of the Well-Being and Levels of user engagement scores for each group and time point

Measure	Condition	N	T0 M (SD)	T1 M (SD)	T2 M (SD)	T3 M (SD)
Wellbeing						
	Past/Fut.	95	35.00 (8.48)	52.14 (10.67)	54.33 (9.32)	55.66 (8.75)
	Fut.	100	34.61 (7.86)	52.78 (10.40)	56.31 (9.26)	56.69 (8.35)
	Control	100	33.58 (9.11)	52.40 (10.67)	56.12 (8.55)	55.62 (7.62)

Engagement with Technology Total scores					
	Past/Fut.	95		30.04 (5.11)	27.95 (6.48)
	Fut.	100		31.98 (4.36)	29.39 (5.56)
	Control	100		30.68 (4.75)	28.94 (6.24)
Behavioural Engagement					
	Past/Fut.	95		9.80 (1.81)	9.54 (2.09)
	Future	100		10.36 (1.56)	10.01 (1.79)
	Control	100		10.21 (1.62)	9.91 (1.93)
Cognitive Engagement					
	Past/Fut.	95		9.88 (2.02)	9.12 (2.43)
	Future	100		10.62 (1.59)	9.56 (2.31)
	Control	100		9.98 (1.96)	9.41 (2.47)
Affective Engagement					
	Past/Fut.	95		10.35 (1.95)	9.23 (2.43)
	Future	100		10.98 (1.76)	9.79 (2.05)
	Control	95		10.49 (1.98)	9.61 (2.21)

Inferential statistics

Differences of user engagement total scores between conditions and over time. The outcomes of the RM-ANOVA showed a significant difference in total scores of user engagement between the measurement time points T1 and T2; F (1,287) = 84.37, p < 0.001, η^2_p = .27. The total scores of user engagement decreased in all three conditions from the T1 to the T2 measurement. With regard to the between-subject analysis, the outcomes revealed no significant main effect for the conditions; F (2,287) = 2.66, p = .072, η^2_p = .018. Next, the interaction between user engagement and the condition was not found to be significant; F (2,287) = 1.11, p = .33, η^2_p = .008 The total mean score of user engagement at the different time points (T1 & T2) and for each condition are illustrated in Figure 3.

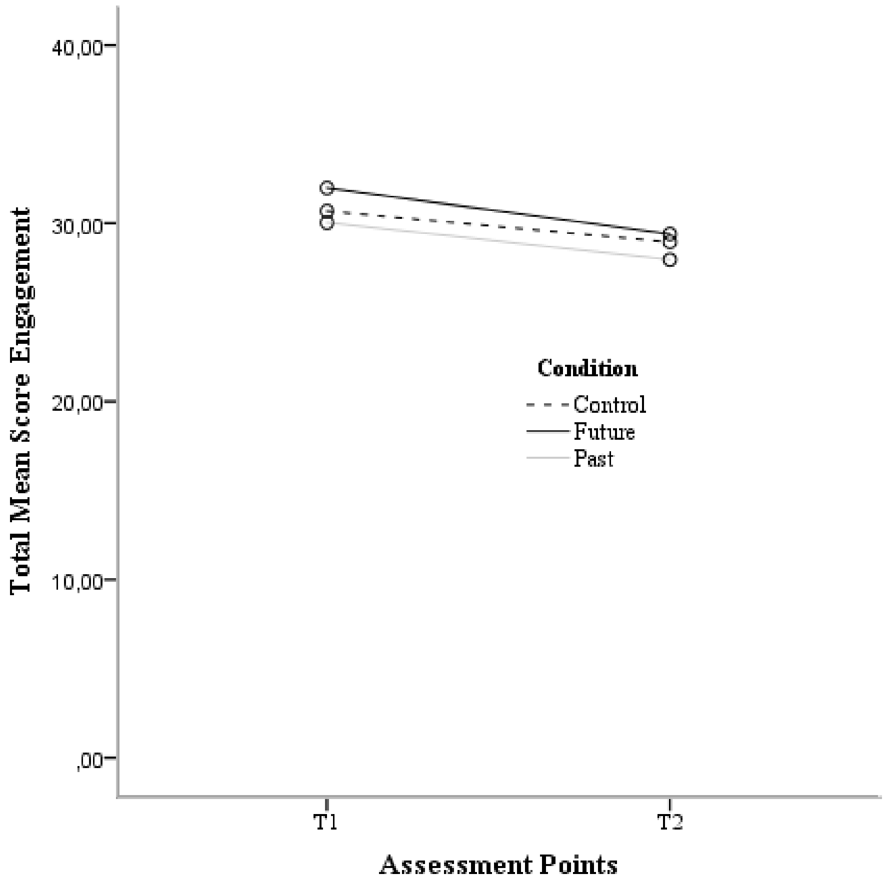


Figure 3. Changes over Time in User Engagement Total Scores among Conditions After One Week (T1) and After Two Weeks (T2)

Differences in levels of user engagement between the conditions and over time. With regard to the dimension of behavioural engagement, the outcomes of the RM-ANOVA showed a significant difference of the behavioural engagement scores between the measurement time points T1 and T2; F (1,287) = 13.40, $p < 0.00$, $\eta^2_p = .045$. The scores decreased from the T1 to the T2 measurement in all three conditions. The between-subject analysis showed no significant main effect for the conditions; F (2,287) = 2.54, $p = .082$, $\eta^2_p = .017$. Finally, the interaction between behavioural engagement and condition was not found to be significant F (2,287) = .14, $p = .86$, $\eta^2_p = .001$.

Concerning the dimension of cognitive engagement, a significant difference between the scores at measurement time points T1 and T2 was found as scores decreased from the T1 to the T2 measurement; F (1,287) = 52.89, $p < 0.00$, $\eta^2_p = .156$. The between-subject analysis showed no significant main effect for the conditions; F (2,287) = 2.54, $p = .082$, $\eta^2_p = .017$. Lastly, no significant interaction effect between cognitive engagement and condition could be found; F (2,287) = 1.49, $p = .226$, $\eta^2_p = .010$.

With regard to affective engagement, the statistical outcomes showed a significant difference of the scores between T1 and T2; F (1,287) = 106.63, $p < 0.00$, $\eta^2_p = .0271$. The scores decreased from the T1 to the T2 measurement time point. The between-subject analysis showed no significant main effect for the conditions, F (2,287) = 2.22, $p = .11$, $\eta^2_p = .015$. Further, the interaction between cognitive engagement and condition was not found to be significant; F (2,287) = .856, $p = .426$, $\eta^2_p = .006$.

Differences in well-being at different measurement time points and among conditions. The outcomes of the RM-ANOVA showed that there was a significant main effect of time on wellbeing; F (3,861) = 757.69, $p < 0.001$, $\eta^2_p = .73$. The Bonferroni adjustment post-hoc analysis showed significant differences (p < .05) between the following assessment points of well-being: T0 and T1, T0 and T2, T0 and T3, T1 and T2, T1 and T3. Only the difference between the well-being scores at the assessment points T2 and T3 was not found to be significant (*SMD* = -.40, $p = 1$). With regard to the between-subject analysis, the outcomes revealed no significant main effect for the conditions; F (2,287) = .35, $p = .70$ $\eta^2_p = .002$. Lastly, the interaction between time and condition was not significant, F (6,861) = 1.17, $p = .32$. An illustration of the well-being scores for the different conditions at the 4 measurement time points can be seen in Figure 4.

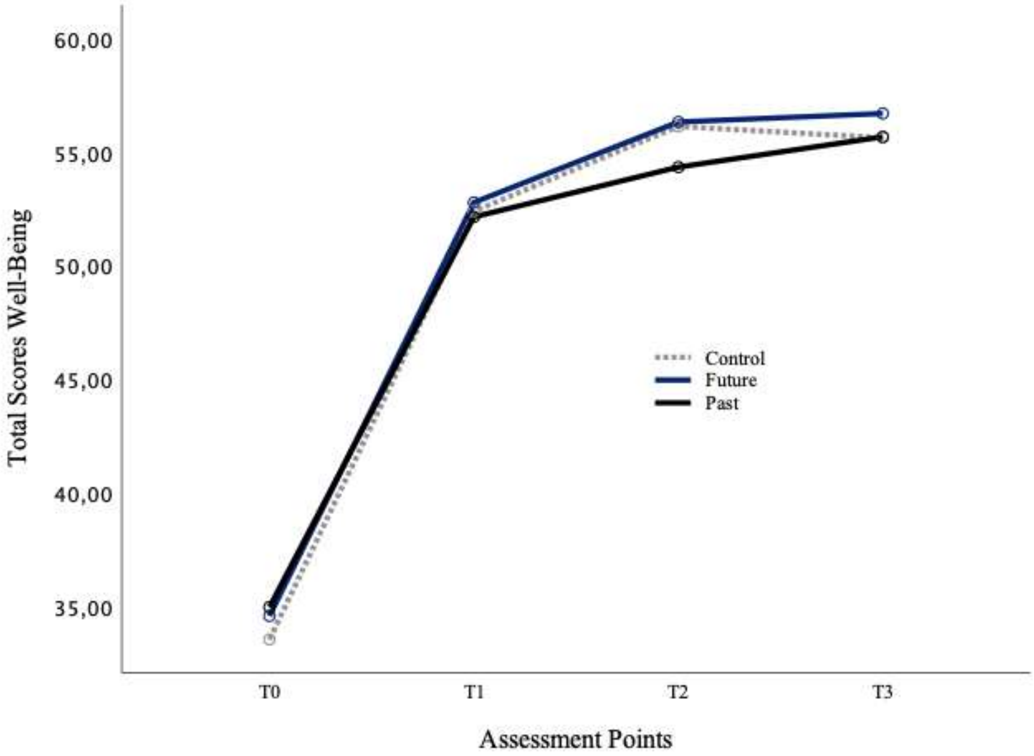
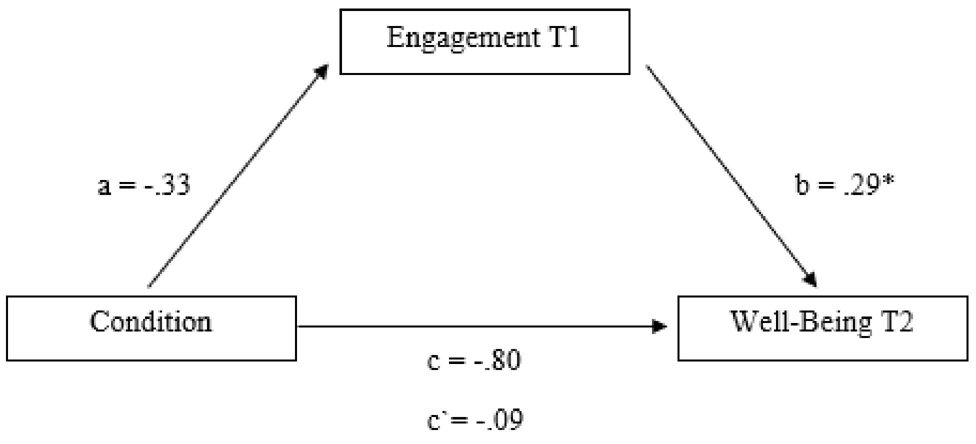


Figure 4. Changes over Time in Well-Being Scores among Conditions at Baseline (T0), After One Week (T1), After Two Weeks (T2) and After four Weeks follow-up Assessment (T3)

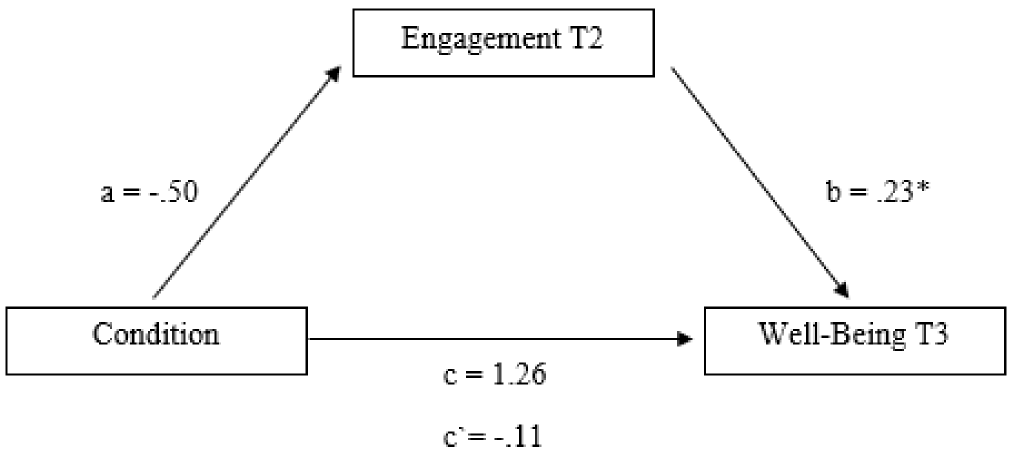
Mediating role of engagement with the BPS on the effect of well-being. The outcomes of the Hayes mediation analysis showed that engagement with the BPS at T1 was not a significant mediator between the two conditions of the BPS intervention (past/future & future condition) and well-being of the participants at T2 (c`: *IE* = -.09, *CI* [-.39, .12). With regard to the different pathways, the condition had no significant effect on engagement with technology at T1 (a: *β* = -.33 *CI* [-1.01, .34)] but the outcomes showed a significant effect of engagement with technology at T1 on well-being at T2 (b: *β* = .29, *CI* [.075, .51) Finally, the direct effect of the relationship between condition and well-being at T2 was also not significant (c: *β* = -.80, *CI* [-2.07, .46]). In Figure 5, an overview of the mediation and the effect sizes of the direct and indirect pathways can be found.

Engagement with technology at T2 did not mediate the effect of condition on well-being at T3 (c`: *IE* = -.11, *CI* [-.38, .09). Further, the direct effect of condition on well-being at T3 was not found to be significant (c: *β* = .126 *CI* [-1.02, 1.27)]. The outcomes also showed that the condition had no significant effect on engagement with technology at T2 (a: *β* = -.50, *CI* [-.1.36, .35), but that engagement with technology at T2 had a significant effect on well-being at T3 *(b: β* = .23, *CI* [.07, .38). An illustration of the single pathways and the direct and indirect effects can be found in Figure 6.



Note: * p <.05

Figure 5. The simple mediation model including the direct effect (c) and the indirect effect (c`) of condition on well-being at T2 and the effect of condition on engagement at T1 (a) and of engagement at T1 on wellbeing at T2 (b)



Note: * p <.05

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Figure 6. The simple mediation model including the direct effect (c) and the indirect effect (c`) of condition on well-being at T3 and the effect of condition on engagement at T2 (a) and of engagement at T2 on wellbeing at T3 (b)

Discussion

This study aimed to investigate whether user engagement and its three subdimensions differed between the past, future and control conditions and among time. Further, it was central to explore, whether user engagement mediated the relationship between condition and well-being. A key finding of this study is that the total scores of user engagement did differ between the two measurement time points, as scores from all three conditions decreased from the assessment after 1 week (T1), to the assessment after two weeks (T2). In line with that, the same pattern was found for the three subdimensions of user engagement, as behavioural, cognitive and affective engagement also decreased from T1 to T2. Central was also that neither the total scores of user engagement differed between the conditions nor the scores of behavioural, cognitive or affective engagement. In addition, this study found that the level of well-being of the participants increased significantly over time in all three conditions. It also showed that the enhancement of well-being persisted after the end of the study when measured at the four-week follow-up assessment. Yet the condition did not influence the enhancement of well-being over time, as no differences between the past/future, future and control condition could be detected. Finally, this study confirmed that user engagement did have an effect on well-being at T2 and T3 but did not mediate the relationship between the conditions and well-being.

Theoretical reflections

This research showed that user engagement, including all three dimensions of user engagement, decreased from T1 to T2 measurement point, which supports the results of prior research. Several studies have revealed that engagement with an intervention decreases over time as it may be that, the longer participants take part in interventions, the more interest they lose in it (Cotter, Durant, Agne & Cherrington, 2014; Nelson Coston, Cherrington & Osborn, 2016). However, for interventions that aim to change behaviour or attitudes, a considerably long intervention is often essential to be effective. Hence, this study confirms that strategies to enhance user engagement, such as engagement promotion through sending reminders or tailoring the intervention to individual needs, are necessary to keep up the user engagement of the participants. That the decrease in user engagement was visible in behavioural, cognitive and affective engagement, shows that strategies to enhance and endure a high level of user engagement over the course of an intervention should cover all three dimensions of user engagement equally.

Another central point of this study was that user engagement did not differ between the three conditions. In line with that, also the scores of the dimensions of user engagement, namely cognitive, affective and behavioural engagement, were not different among the three conditions. As several factors can influence the amount of user engagement, it was of interest to explore whether user engagement and its dimensions would differ between the three conditions. It was chosen to investigate this issue in an explorative way, as reasons for, as well as, against possible differences in user engagement among the conditions were found. For example, O´Brien and Toms (2008) stated, that the difficulty of a task might have an influence on the user engagement of participants. They theorized, that an appropriate amount of challenge through the intervention can positively affect the intrinsic motivation of participants and hence their willingness to engage with the technology and to believe, that the technology will support them to reach their goals (O'Brien & Toms, 2008). As the different conditions require different skills, such as recall skills for the past condition and imagination skills for the future condition, it would have been possible that the interventions differed in their level of difficulty.

However, that such an effect did not occur in this study could be explained by the fact that both, the past and future condition made use of imagination and visualisation skills, as the past condition also included the exercise to visualize and document the BPS in the future during the second week of the intervention. Thus, the level of difficulty might not be that different among conditions. However, as the level of difficulty for the tasks of each condition was not assessed in this study, no conclusive inferences can be made at that moment. Besides the difficulty of a task, other factors can also influence user engagement such as the amount of human support or the length of a study (Baumel & Kane, 2018), which were the same for all three conditions. Thus, those factors would support the finding of this study, namely that no differences in user engagement among conditions were detected.

Looking more deeply into the subdimensions of user engagement, it becomes apparent that no pattern, other than that the three subdimensions were equally present, could be detected. This is in line with user engagement theory which postulates that user engagement consists of behavioural, affective and cognitive engagement (Kelders et al., 2020). Consistent with that, the BPS mobile application succeeded to address the different dimensions of user engagement and did not only cover one of them. According to Kelders et al. (2020), a technology should aim to appeal all three subdimensions of user engagement to ensure that participants do not have to depend on one dimension of user engagement that does not fit their individual engagement style. Thus, it can be concluded that the personal engagement styles of participants could be considered by covering all three dimensions of user engagement.

Furthermore, this research showed that well-being increased in the two intervention conditions over time and endured after the end of the intervention, at the 4-week follow up assessment which is in line with prior research, as an enhancement of positive emotions and well-being through a BPS intervention was detected in several prior studies (Peters, Meevissen & Hanssen, 2013; Carillo et al., 2020). Surprising was that the well-being scores of participants assigned to the control condition also increased over time, which is against what was expected. An explanation for this occurrence could be that this study made use of an active control condition and matched the expectations of all three groups by informing the experimental condition as well as the control condition about the intervention purposes. According to Boot et al. (2013), most psychological interventions do not consider to match the expectations between the control and experimental condition, leading to possible design flaws that can threaten the results and the effectiveness of a study. When comparing this study to prior research, some studies integrated an active control condition into their study but did not consider to match the expectations for all conditions to rule out a possible placebo effect (Liau et al., 2016; Peters et al., 2013). Similar to this study, Carillo et al. (2020) who also included an active control condition and provided information about the purpose and the expectations of the studies for all groups, found no significant differences between the control and experimental conditions.

However, when interpreting the results from the present study, it should be considered that the study outcomes could have been threatened by the fact that a mobile application was used as a delivery method for the BPS intervention. Even though previous research has confirmed that the BPS intervention was also effective when delivered online (Layous et al., 2013), this study is one of the first that makes use of a mobile application as a delivery method. Most online interventions that investigated the effectiveness of the BPS intervention used various web platforms or PowerPoint files as tools to convey the intervention or SMS messages as reminders to continue with the exercises (Enrique, Bretón-López, Molinari, Baños & Botella, 2018). A possible limitation of the use of mobile applications to deliver psychological interventions are considerably high dropout rates and low adherence to the application, compared to in-person intervention that might reduce the effects of the intervention (Andersson & Titov, 2014). Further, a lack of guidance through a licensed professional might limit the effectiveness of mobile applications, as human support and a therapeutic relationship showed to be an important factor for the effectiveness of psychological interventions (Prentice & Dobson, 2014). Even though other positive psychology interventions have found to be effective when delivered in the form of mobile applications (Bolier & Abello, 2014), there is a lack of research regarding the effectiveness of BPS applications. Therefore, future studies should investigate whether mobile applications can also produce positive changes in participants.

That no differences in the conditions were found regarding the level of well-being and user engagement accounts for an explanation why no mediation effect of engagement with technology on the relationship between condition and well-being could be confirmed within the present research. Yet, user engagement did predict well-being in this study which is in accordance with findings reported by Yardley et al. (2016), who stated that a high amount of engagement with technology often holds as a precondition for an intervention to be effective. As no prior research looked into the impact of user engagement on the effectiveness of a BPS intervention delivered by a mobile application, this result provides evidence of the importance of engagement with the technology for a BPS intervention to be effective. This result is in line with other studies that confirmed the important role of user engagement on the effectiveness of interventions. For example, Lippke, Corbet., Lange, Parschau and Schwarzer (2016) confirmed that the amount of engagement had an effect on a behavioural intervention about promoting a healthy diet.

Strengths and Limitations

A strength of this research is that the influence of user engagement on the effectiveness of a BPS mobile-based intervention has been confirmed within this study, which has not been explored in prior studies. This new understanding of the importance of a high amount of user engagement with the BPS provides the chance to adjust and improve the BPS exercises by integrating strategies to enhance user engagement, and thus the effectiveness of the intervention. This study also generated the new knowledge, that the three dimensions of user engagement equally constituted the score of user engagement, indicating the importance of each dimension for the BPS intervention. That the present study made use of an active control condition is another strong point of this research. To make conclusive inferences about the effectiveness of a psychological intervention, the treatment conditions must be compared with a control condition that holds for effects caused by factors other than the treatment (Boot, Simons, Stothart, & Stutts, 2013). Thus, including a control condition helps to test whether the positive effects of the intervention resulted from a so-called placebo effect. In line with that, this study also ensured that participants from all conditions were equally informed about the purpose of the study and had matching expectations, which is another factor that needs to be considered when controlling for a placebo effect (Boot, Simons, Stothart, & Stutts, 2013).

Furthermore, another benefit of this study is the use of an online positive psychology intervention for research purposes. Online interventions bring the advantage to reach broader populations and to have lower delivery costs compared to in-person interventions while being as effective as in-person interventions (Baños et al., 2017). Next, that this study followed a randomized control trial can also be considered as a strong point. Randomization was successful in the present research as the three groups did not differ in the sample size or their demographic characteristics. Thus, the threat of differences between the experimental conditions and the control condition can be ruled out for this study. Finally, this study is one among a few that looks into the temporality aspect of the BPS condition by including a past condition in the research, which can also be seen as a strong point.

However, this study also has some potential limitations that should be taken into consideration when interpreting the findings of this study. For instance, the two intervention conditions were not completely different from each other, as the past/future condition also included a one-week training concerning the best possible self in the future. To make stronger inferences about whether the temporality has an effect on user engagement and hence of the effectiveness of the BPS intervention, it would be advisable to draw up a study with one experimental group that only focuses on the BPS and another experimental group that only involves the best past self. For example, Carillo et al. (2020) included a Best Past Self condition in their study, in which participants were asked to focus on the best past self for two weeks without a switch to the future best self after one week.

Furthermore, a central limitation of this study is that the final sample cannot be generalised to the whole population. Besides the fact, that the majority of the participants were highly educated women, which makes the sample less generalisable to the whole population, the recruitment strategy of this study may have resulted in a very homogenous sample. Since participants were recruited through Facebook, which represents a social media platform, only Facebook users took part in this study. Hence, only people who were familiar with technology, as the use of Facebook requires to possess a technology with an internet connection, such as a smartphone, were analysed in this study. This could account for the great similarity of user engagement in this study.

Finally, that the amount of user engagement was only measured with the TWEETS questionnaire can also be considered as a limitation in this study (Kelders, Kip & Greeff, 2020). Especially the amount of objective adherence to the technology could have additionally be measured in the application to provide data about the actual usage of the application. Tracking the actual amount of user engagement could provide valuable information about the amount of adherence to the application and could complement the information gained from the TWEETS questionnaire. The objective adherence could then be compared with the amount of user engagement and new insights can be gained through this. For example, an assessment of objective adherence would indicate the actual amount of engagement with the technology, whereas engagement levels through questionnaires can only represent a subjective prediction of engagement (Kelders, Kip & Greeff, 2020). Therefore, comparing objective adherence and subjective engagement with the technology could provide information about whether participants who scored high engagement questionnaires also adhered more to the technology.

Practical implications and directions for future research

Based on the results of this study, some theoretical and practical implications can be derived. First of all, future research should integrate a more diverse sample, namely participants with a different technological background, to investigate whether the homogenous sample of this study accounted for the great similarity in user engagement scores or if other factors could be responsible for that. Further, as this study confirmed the importance of user engagement for the BPS mobile application to be effective, future studies should continue to research how user engagement can be enhanced effectively. With regard to the temporality aspect of the BPS intervention, it is advisable to design a study with a pure past and future condition, to compare those two groups more effectively. This would make it easier to investigate whether user engagement is affected by the different time frames, as the past and future condition could be completely distinguished. To explore whether the difficulty of a task can have an effect on the amount of user engagement, future studies could assess the perceived level of difficulty of the BPS exercise. Then, the association between user engagement and the perceived level of difficulty could be explored and new insights about the underlying mechanisms of user engagement could be gained.

Besides the theoretical suggestions for future research, this study also revealed some practical implications. To improve the delivery of the intervention using a mobile application, human support could be included in the intervention, for example through a chat function, in which questions could be asked and answered by professionals. According to the user engagement theory of Bender (2014), human support can enhance the amount of engagement to the intervention. Hence, it could be possible, that participants make use of a chat function to ask questions about the intervention instead of dropping out of the study immediately when being insecure about taking part in the study. Thus, integrating human support into the application could reduce dropout rates and enhance engagement with technology.

In addition to that, this study confirmed a central aspect of user engagement theory, namely that the amount of engagement naturally decreases over the course of an intervention due to a loss of interest (Nelson, Coston, Cherrington & Osborn,2016). To overcome this issue and to ensure that a high amount of user engagement persists till the end of the study, a practical implication would be to enhance user engagement by focusing on the subdimensions of user engagement. As the study revealed that affective, behavioural and cognitive engagement were equally present among the participants, it can also be advised to design future BPS interventions in a way that enhance engagement in all three dimensions. For example, to enhance behavioural engagement, the participants could determine how the exercises would fit best in their daily routine and according to that, the time frame of the intervention could be adapted. Affective engagement could be promoted by inducing more positive emotional experiences through the BPS intervention. This could be reached through rewarding participants when they completed an exercise or by promoting social exchange between the participants to share their experiences. Finally, cognitive engagement could be tackled by educating the participants about the advantages of positive psychology interventions to ensure that the participants believe that the BPS intervention supports them to reach their goals.

Furthermore, as this study did not find differences in well-being scores between the past and future BPS condition, the outcomes support the assumption that the temporality factor is not that essential for the BPS condition to be effective, which was already predicted by Carillo et al. (2020). Different practical implications can be drawn from this finding: For example, as stated in Carillo et al. (2020), participants individual preferences regarding the temporal frames should be considered in the future, to ensure that participants benefit as much as possible from the BPS intervention. People who are anxious about their future due to severe, life-threatening illnesses, might prefer to take part in an intervention that focuses on the best self in the past instead of concentrating on the future. Hence, participants should be allowed to choose for themselves what kind of version of the BPS fits their individual needs the best.

Conclusion

In conclusion, the present study explored whether levels of user engagement differed between the conditions, over time and whether user engagement affected the intervention outcomes. The research has enhanced our understanding that future studies should look more deeply into the influence of user engagement on the outcomes of BPS interventions, as an effect on well-being was found. Further, as user engagement and its subdimensions decreased over the course of the intervention, future research should focus on tackling this issue by developing strategies to enhance cognitive, behavioural and affective engagement. The study also revealed that user engagement did not differ between the conditions, which could be explained by the fact that in this study, temporality was not found to be an essential factor for the BPS intervention to be effective. However, the generality of the current results must be established by future research that looks more deeply into the impact of user engagement on the effectiveness of the BPS intervention. In general, exploring the working mechanisms of BPS is essential because only when professionals understand how and why the BPS is effective to increase well-being, the interventions can be used most effectively and can be adapted for certain target groups and individual needs. Finally, exploring the role of user engagement may not only be relevant for the effectiveness of the BPS intervention but the newly gained knowledge can also be applied for developing other online psychological interventions.

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