Components of engagement and their effect in a personalized wellbeing intervention

Master Thesis

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Abstract

Previous research suggests that participants' levels of engagement and the personal fit of interventions to their preferences play a crucial role in the effectiveness of digital health interventions. Building upon this knowledge and utilizing the TWEETS scale, which assesses engagement with eHealth technologies based on affective, behavioural, and cognitive components, the current study investigated the impact of these components on a wellbeing intervention. Specifically, the study examined whether personalization influenced the components of engagement and wellbeing measures, and whether these components mediated the effect of personalization on wellbeing measures. Personalization was achieved through a randomized controlled trial design, where participants in the experimental group were assigned the version of the intervention that best matched their indicated preferences. However, linear mixed models revealed no significant effects of personalization on wellbeing or the components of engagement. Additionally, no mediation effects of the three components between personalization and wellbeing were found. Notably, the mediation analysis revealed a significant effect of the behavioural component on wellbeing, although no such relationship was observed for the other two components. Moreover, the results showed an improvement in wellbeing from baseline to post-intervention, regardless of personalization. Both the experimental and control groups showed a continuous decline in engagement throughout the course of the intervention. Given that the current personalization procedure did not yield significant effects, it is recommended for future research to focus on dynamic personalization procedures. Moreover, further investigation into participants' motivation within the context of engagement and the effects of different engagement components on psychological constructs other than wellbeing is advised.

Keywords: digital health intervention, engagement, personalization, wellbeing, randomised controlled trial

Components of engagement and their effect in a personalized wellbeing intervention

Wellbeing is increasingly being recognized as an important aspect of overall health. The online APA dictionary of Psychology defines wellbeing as “a state of happiness and contentment, with low levels of distress, overall good physical and mental health and outlook, or good quality of life” (n.d.) The relationship between mental wellbeing and mental health is also made evident by the WHO, who states that “mental health is a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community” (2022).

In mental health care the importance of wellbeing per se was long not regarded as much as it is the case nowadays. Instead, the focus was more on treating mental illnesses and reducing their symptoms. However, as research in the field of positive psychology continues to grow, the relationship between wellbeing and mental illness has been researched in more detail. In particular the two-continua model (Keyes, 2005) has been developed which states that while mental wellbeing and mental illness are related concepts which even share some similar antecedents, they are yet distinct from each other. According to this model, a person can for example have low levels of mental illness symptoms yet still not score high on wellbeing. From this differentiated view of the relationship between mental wellbeing and mental illness, it may therefore be concluded that classical approaches to the treatment of symptoms may alleviate mental illnesses, but do not necessarily improve wellbeing. This requires new approaches such as those provided by positive psychology (Slade, 2010).

Moreover, next to the two-continua model, Keyes (2005) established a wellbeing model which consists of three components: emotional wellbeing (feelings of happiness and satisfaction with life), psychological wellbeing (a positive individual functioning in terms of self-realization) wellbeing and social wellbeing (a positive societal functioning in terms of being of social value) (Westerhof & Keyes, 2010). To promote the improvement of these components and thereby reaching an overall increased wellbeing is relevant for a variety of reasons. For instance, high levels of wellbeing have been found to be protective against the development of mental disorders such as depression (Wood & Joseph, 2010), especially in older people. These effects were also observed in a longitudinal study which found high levels of wellbeing to significantly reduce the risk of developing mood and anxiety disorders in a representative adult sample (Schotanus-Dijkstra et al., 2017). The importance for promoting wellbeing also becomes apparent in a clinical context as it was also found that wellbeing can not only be protective but also positively influence the recovery from mental illness such as anxiety disorders (Schotanus-Dijkstra et al., 2019). Moreover, wellbeing not only plays a role in a personal and clinical context but also on a larger societal scale. For example, Maccagnan et al. (2019) found that wellbeing not only has positive linkages to health but also to other co-benefits such as prosocial and environmental-friendly behaviour, better work performances and higher educational achievements, which may be of particular interest for the target group of the current study, which is university students.

To improve people's wellbeing different interventions have been investigated regarding their efficacy. Van Agteren et al. (2021) compiled a systematic review and meta-analysis of over 400 psychological interventions that aimed at improving mental wellbeing. They found that mindfulness based and multi-component positive psychological interventions in general had the highest efficacy compared to other interventions, such as cognitive-behavioural and acceptance and commitment therapy-based interventions. Multi-component positive psychological interventions are described as interventions that consist mainly or entirely of positive psychology exercises such as using strengths or gratitude, delivered over an extended period of time (van Agteren et al., 2021). Small and moderate effect sizes were found in both clinical and non-clinical populations. Moreover, it was found that group-based interventions demonstrated the greatest effect when compared to individual and technology-based interventions. Thus, it may either be that group-based interventions are just more effective or that the full potential of technology-based interventions has not been reached yet and more research on the topic needs to be done to make them more effective. The current research is concerned with the latter possibility.

Digital health interventions

One way of administering such wellbeing interventions are digital health interventions (DHI), which are "interventions delivered via digital technologies such as smartphones, websites, or text messaging" (Murray et al., 2016). DHIs offer a variety of benefits compared to conventional interventions. For instance, healthcare systems can benefit from them since they are cost effective, safe, and scalable to a large number of patients (Murray et al., 2016). In the case of wellbeing this is not only important for patients who seek an improvement in wellbeing but also for the public in general since delivering an intervention digitally is becoming more suitable with a wide spread of smartphones nowadays.

While many people still hesitate to seek psychological help when they are in need of it, DHIs can furthermore ease the access for them because they don't have to get in contact with a psychotherapist, which they might often have fears and doubts about (Taylor-Rodgers & Batterham, 2014). Moreover, using DHIs instead of conventional therapies also allows patients to bypass possible long waiting lists (Espie, 2009) or alleviate symptoms for a while and serve as a suitable solution until in-person help is accessible (Health Europe, 2020). In the context of wellbeing interventions this seems promising since an improved wellbeing may later support the treatment of mental illnesses (Schotanus-Dijkstra et al., 2019).

Despite the promising benefits that DHIs bring, there are a few issues to keep in consideration. In a systematic overview Lehtimaki et al. (2021) found that while over the past few years an increasing number of DHIs have been developed, only a fraction of them is grounded in empirical evidence which compromises effectiveness and may even have detrimental effects. Moreover, those DHIs which have been developed in an evidence-based manner still suffer from minimal adherence in a real-world setting. For instance, Baumel et al. (2019) found a median retention rate of merely 3.9% over a span of 15 days in a systematic analysis of mental health apps. One factor that may contribute to such low retention rates may be that DHIs are often not specifically personalized to the users' needs.

Personalization

While in conventional psychotherapy one of the most important factors for successful treatment is the therapeutic alliance between the therapist and the individual client (Flückiger et al., 2018), in a stand-alone DHI, where a real in-person therapist is absent, this crucial factor is missing. Therefore, it is important to focus on other factors to ensure effectiveness. One important factor in this context is a personal fit of the DHI to the user's needs. This can be reached by personalizing factors such as content, feedback and design of an intervention (Kelders, 2019). Specific content based on distinctive psychological theories (e.g., positive psychology or cognitive-behavioural therapy) may thus be more fitting to a person if it matches his or her values and beliefs (Hyland & Whalley, 2008). Moreover, different ways of delivering feedback (e.g., text-based or video-based) within an intervention can differ in their effectiveness depending on user's preferences and needs (Kelders et al., 2015; Talbot, 2012). Lastly, it was found that a gamified design can be more engaging for some individuals (Hamari et al., 2014). However, while these approaches to personalization can be effective, not every approach works for every person, and it is yet unclear how to best match individuals to a certain version. One way of doing this could be by measuring individuals' engagement in the intervention (Kelders, 2019).

Engagement

While the personalization of wellbeing DHIs can have an effect on outcome measures, another major factor that has yet to be explored in more detail is the role of engagement and how it effects user's outcome measures in wellbeing DHIs. Although DHIs have a lot of advantages, as mentioned above, a limitation can be that users are often not fully engaged in the intervention, which can minimise its' effectiveness (Perski et al., 2017). To increase engagement in DHIs different factors may be effective such as notifications (Kelders, 2019) or gamification (Hamari et al., 2014).

To investigate what constitutes engagement and the role it plays in the context of DHIs, Kelders et al. (2020a) conducted a comprehensive systematic scoping review. They found that while engagement has often been viewed as a behavioural concept, concerned with for example how often and for how long a DHI is used, a more comprehensive view includes an affective and a cognitive component as well.

Kelders (2019) distinguishes these three components as follows: the affective component refers to the emotional response experienced when observing progress, or the absence thereof, and is connected to emotions experienced during the use of the intervention, such as enjoyment. The behavioural component encompasses not only adhering to the intervention as intended, but also emphasizes the importance of establishing a habitual routine for incorporating the intervention and exercises into one's daily life. Lastly, the cognitive component pertains to how the intervention can effectively assist individuals in achieving their goals, such as enhancing their overall well-being. Based on these findings the TWente Engagement with Ehealth Technologies Scale (TWEETS) was developed which measures the engagement with eHealth technologies based on its behavioural, cognitive and affective components (Kelders & Kip, 2019).

Current study

Considering Van Agteren et al.'s (2021) findings of the efficacy of interventions for promoting wellbeing, and the importance of personalization in the use of DHIs, it is worthwhile exploring the role of engagement and its' components in personalized DHIs. With both a personal fit of an intervention effecting its outcome measures and engagement also being important for its effectiveness it raises the question of what the underlying mechanisms are. One explanation might be that engagement with its three components serve as a mediator in the relationship of personalization and effectiveness of an intervention. While Kelders et al. (2020a) established the three components of engagement in the context of eHealth interventions and we assume them to be constituents of engagement as a whole, a possible mediating effect of engagement between personalization and wellbeing outcomes would therefore most likely be attributed to one or more of the components. Therefore, the current study investigates if personalization of a wellbeing DHI has an effect on its outcome and what the role of engagement and its' behavioural, cognitive and affective component in this context are. The research questions are:

RQ 1: *Does a personalized 2-week wellbeing intervention lead to a larger increase in wellbeing outcomes compared to a control group?*
RQ 2: *Are there differences as to how personalization effects the three different components of engagement (behavioural, cognitive, affective) compared to a control group?*
RQ 3: *Do the three components of engagement mediate the effect of personalization on wellbeing?*

Methods

Design

This RCT study is a part of a broader research project being conducted by Kelders at the University of Twente with the aim of establishing a credible personalization strategy for eMental Health applications. The broader research employed three intervention and technology factors (ITFs) - *content*, *design* and *feedback* - which were also used in the current study. Participants were randomized into a personalized and non-personalized group and took part in the intervention for a duration of 21 days. On day one, three and seven they were asked to fill out a short questionnaire measuring their level of engagement in the intervention. Additionally, they were asked to complete surveys at three different time points: at the start of the study (T_0), after the intervention (T_1), and at follow-up (T_2). To answer the research questions quantitative data analysis was applied. The study was also approved by the Ethics Committee of the Faculty of Behavioural, Management, and Social Sciences (BMS) at the University of Twente (number: 220083).

Participants

Participants were selected through convenience sampling and the University of Twente's Test Subject Pool System (SONA), where they could earn credits for their participation in the research. To be eligible, participants had to be fluent in English, own a smartphone and be at least 18 years old. Those who scored less than five points on the Patient Health Questionnaire-9 (PHQ-9) or the Generalized Anxiety Disorder Questionnaire-7 (GAD-7) were excluded from the sample. Additionally, participants who failed to complete the baseline survey or did not register for the TIIM App were also excluded. In line with the intention-to-treat-principle, those who discontinued participation in the TIIM App intervention were still included in the study, as it can be speculated that they were not engaged enough in the personalized or randomized versions of the DHI which in turn gives valuable information about the interplay of personalization and engagement.

Procedure

The data on which this study is based was collected between February and May 2022 and was offered students for participation through the University of Twente's SONA system. After reading and signing the informed consent participants filled out a baseline questionnaire which included demographical questions, the MHC-SF (Mental Health Continuum-Short Form) (Appendix A) and an adjusted version of the TWEETS questionnaire (Table 1). After finishing the baseline questionnaire, participants were screened for eligibility criteria. Those who qualified were then asked to download and register for the TIIM app through which the intervention was carried out and were given additional instructions via email. Participants were randomly assigned to either the experimental group or the control group. The experimental group received the best fitting version of the intervention based on their TWEETS baseline questionnaire responses, while the control group was randomly assigned to one of the 27 intervention versions. Participants were expected to complete the daily modules of the intervention within 14 consecutive days but were given up to 21 days to allow for some missing days in between. The researchers monitored their progress and reminded inactive participants through email. All participants who had signed up and began the intervention were sent an email with a link to a post-questionnaire after 21 days. In this questionnaire, they were once more asked to complete the MHC-SF and a modified TWEETS questionnaire (Appendix B). Eight weeks after baseline measurement, they received another email with a link to the follow-up questionnaire. To maintain accurate data tracking, participants were asked to create a unique identity code to enter before each response.

Intervention

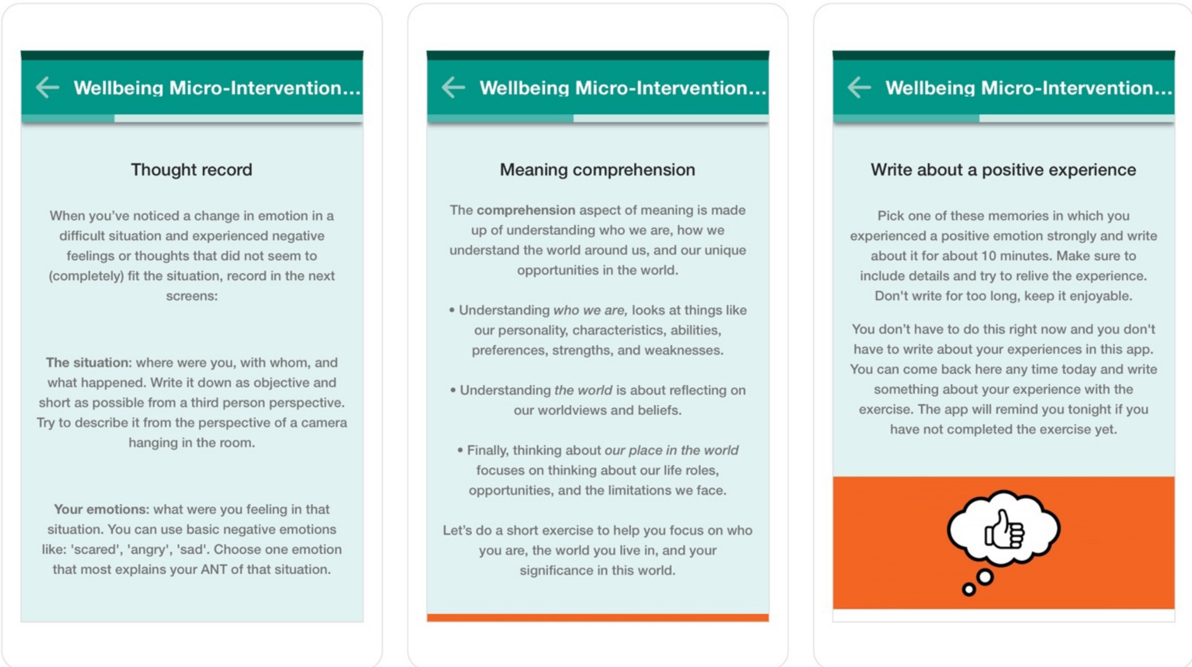
27 different versions of the intervention were administered through the TIIM app, an app for smartphone users that was designed by the BMS lab of the University of Twente to conduct different kinds of interventions. The procedure of every version was the same, following an introduction to the intervention and its' specific approach, a pre-exercise assessment of wellbeing, the daily exercise, and post-exercise feedback. Participants repeated this procedure on 14 days with varying exercises.

The different structure of the 27 different versions of the app results from different combination possibilities within each version. There are three different *factors*, which are *content*, *design* and *feedback*. Each of these three *factors* in turn has three different variations, which are called *options*. A specific combination of *options* across the *factors* is defined as a *version*. These 3x3x3 *options* across the *factors* thus resulted in 27 different *versions*. Each version included the same combinations of options for the complete duration of the intervention.

The factor *content* and therefore the exercises themselves differed based on which therapeutic approach was chosen. The three different options followed either a meaning intervention approach, cognitive behavioural therapy or positive psychology. An example of a positive psychological exercise is the use of personal strengths in which different ways of applying strengths were introduced and the participants were encouraged to apply them accordingly. Afterwards they wrote down a short reflection on their experiences. Figure 1 illustrates the three different options of the factor *content*.

Figure 1

Illustration of exercises on one day of the intervention based on the three different content options



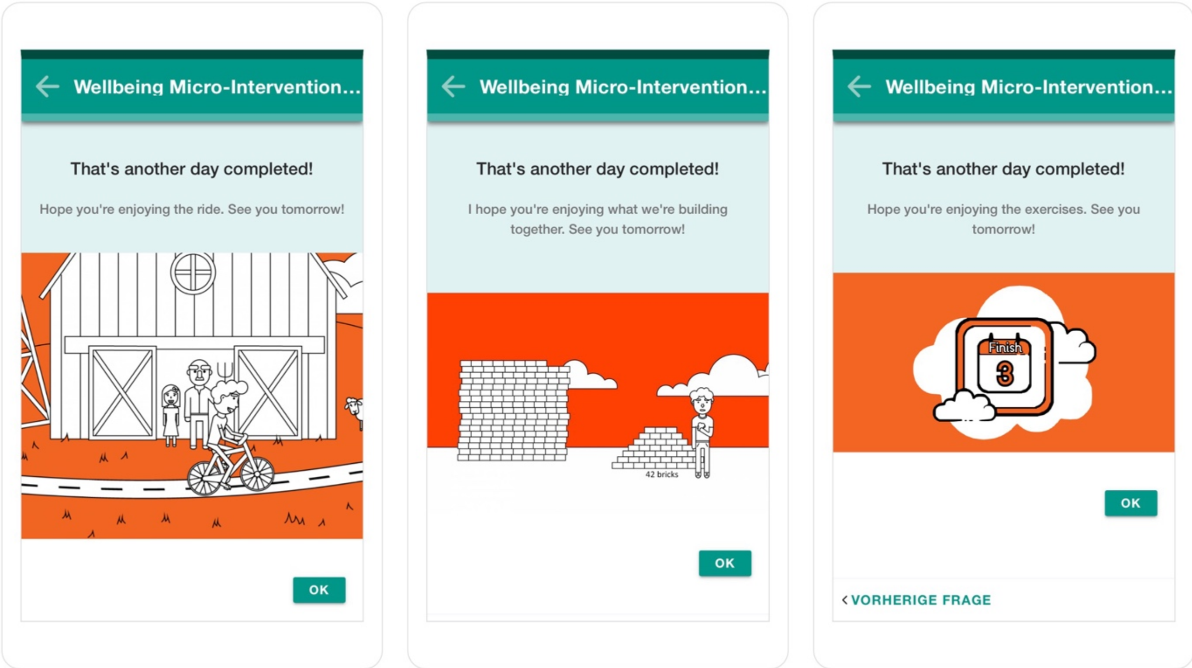
Note. Options from left to right: cognitive behavioural therapy, meaning intervention and positive psychology.

The factor *design* differed in the options non-competitive gamification, competitive gamification and non-gamified. The non-competitive gamification option consisted of a cyclist avatar who cycled through different scenarios, following the course of the intervention. The competitive gamification option consisted of a pile of bricks building up to illustrate the process being made and the number of bricks which have already been moved.

Lastly, the non-gamified option showed the number of days the participant has already been participating in the intervention on a calendar illustration. Figure 2 illustrates the three different options of the factor *design*.

Figure 2

Illustration of the different design options after an exercise has been completed

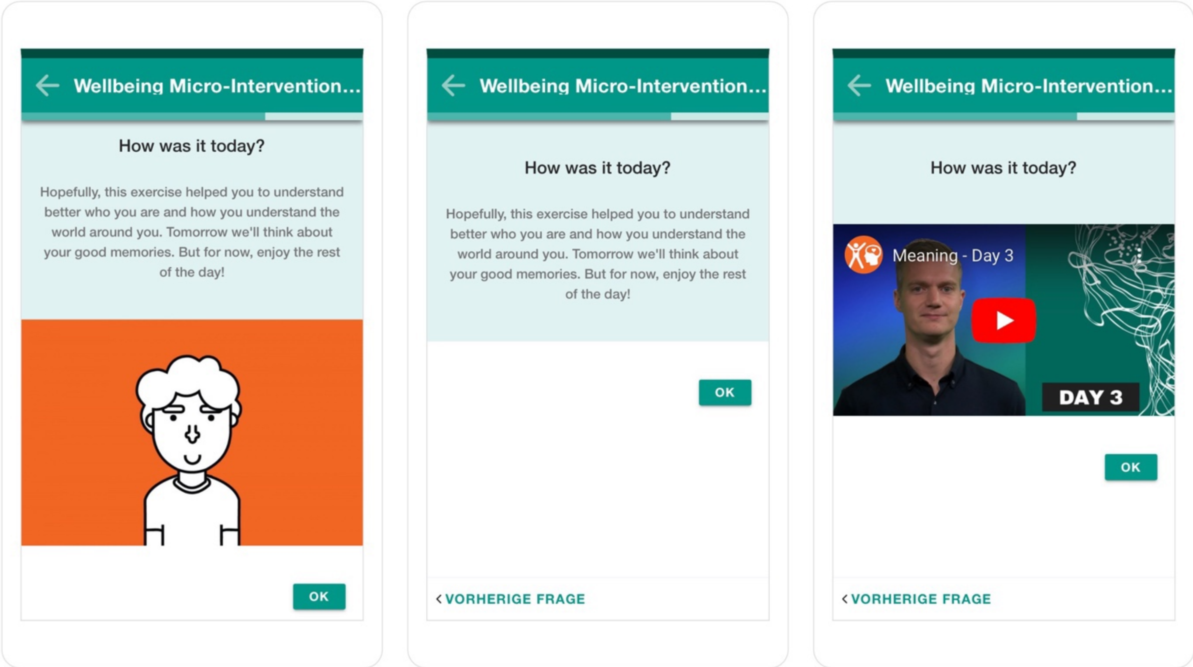


Note. Options from left to right: non-competitive gamification, competitive gamification and non-gamified.

The three different options for the factor *feedback* had the exact same content but were presented in three different ways: plain text, text with an avatar and a video from a psychological counsellor. Feedback was given after each module of the intervention was completed. Figure 3 illustrates the three different options of the factor *feedback*.

Figure 3

Illustration of the different feedback options



Note. Options from left to right: text with an avatar, only text and a video from a psychological counsellor.

Personalization of the intervention

The answers of the baseline measures of the TWEETS questionnaire were used to determine each participant's personal preferences. The items were rephrased (Table 1). The process of evaluating participants' preferences was conducted by asking them to rate their level of engagement for each option of the factors content, feedback, and design by presenting them templates of the options. The factor content for instance included a description of the relevant theory and a sample exercise for each of the three options (meaning intervention, cognitive behavioural therapy and positive psychology). For instance, for the meaning intervention a description was provided which explains it as: *"A meaning intervention is a type of intervention that aims to help patients establish a sense of meaning in life that allows people to gain personal clarity around the value of their life as a whole and to develop a sense of overarching purpose."*

The total scores of each option under each factor were calculated and the highest score was used to indicate a participant's best fitting option. In case of the same score between multiple options under a factor, one option was chosen randomly using random.org. The participants in the experimental group were given the most suitable intervention of the

27 versions based on their preferences while participants in the control group were randomly assigned to a version.

Table 1

Modified TWEETS items for baseline questionnaire, measuring engagement scores in regard to content and app characteristics

Item	Content-specific TWEETS	App-specific characteristics TWEETS
1	Using an app with this *content* can become part of my daily routine.	Using this *version of the app* can become part of my daily routine.
2	The *content* of this app is easy to use.	This *version of the app* is easy to use.
3	I will be able to use an app with this *content* as often as needed to improve my well-being.	I will be able to use this *version of the app* as often as needed to increase my well- being.
4	An app with this *content* will make it easier for me to work on increasing my well-being.	This *version of the app* will make it easier for me to work on increasing my well-being.
5	This *content* motivates me to increase my well-being.	This *version of the app* motivates me to increase my well-being.
6	This *content* will help me to get more insight into my well-being.	This *version of the app* will help me to get more insight into my well-being.
7	I will enjoy using an app with this *content*.	I will enjoy using this *version of the app*.
8	I will enjoy seeing the progress I make by using an app with this *content*.	I will enjoy seeing the progress I make in this *version of the app*.
9	An app with this *content* will fit me This *version of the app* will as a person.	This *version of the app* will fit me as a person.

Note. The factor content was evaluated using the TWEETS specifically tailored for the content options meaning intervention, cognitive behavioural therapy and positive psychology. The factors design and feedback were assessed using the app-specific characteristics TWEETS.

Materials

Engagement

Engagement was measured with the TWEETS questionnaire (Kelders et al., 2020b). The questionnaire includes nine items rated on a 5-point Likert scale from 0 (strongly disagree) to 4 (strongly agree) (Appendix C). This results in a total score range from 0 (not engaged) to 36 (strongly engaged). Moreover, the scale consists of three subscales, measuring the affective, behavioural and cognitive component of engagement. Each subscale consists of three items. The psychometric properties of the TWEETS questionnaire are good with a high internal consistency and a reasonable test-retest reliability (Kelders et al., 2020b). Internal consistency was also high in the current study for engagement as a whole ($\alpha = .93$) as well as the affective ($\alpha = .88$), behavioural ($\alpha = .76$) and cognitive component ($\alpha = .87$).

Mental wellbeing

To assess participants' wellbeing, the MHC-SF was used which measures the emotional, psychological and social dimension of wellbeing (Keyes, 2002) (Appendix A) with 14 items. The total sum score ranges from 14 to 84 and item scores range from 1 (never) to 6 (every day) on a 6-point Likert scale. One example item for measuring psychological wellbeing would be "During the last month, how often did you feel that your life has a sense of direction or meaning to it?" (item 14). The psychometric properties of the MHC-SF are good with a high internal consistency and moderate test-retest reliability (Lamers et al., 2011). The current study also revealed a high internal consistency with $\alpha = .89$.

Data preparation and analysis

The pre-, post and follow-up data was imported into the Statistical Package for the Social Sciences (IBM SPSS Statistics 27). The same was done with the data from the TIIM app. Next, the datasets were merged on the variable participant ID code. The resulting dataset was then cleaned from cases with duplicate participant ID codes by retaining those cases who had more complete answers given. If both had the same number of complete answers the one which was filled out earlier was retained.

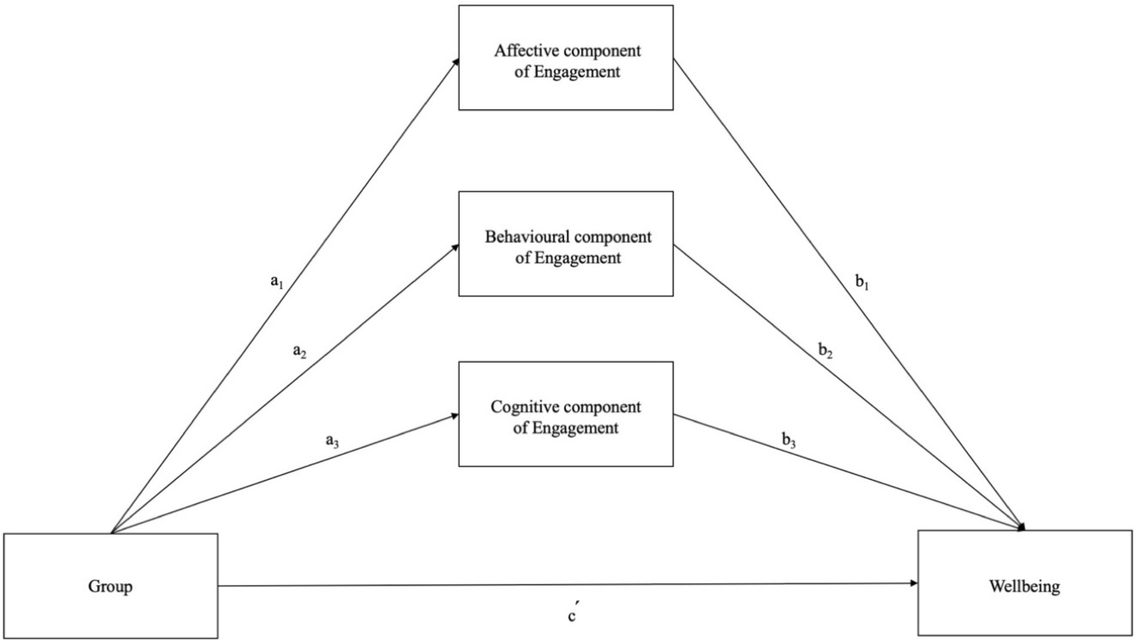
Thereafter, sum score variables for engagement and wellbeing measures were created for each measured time point. Additionally, sum score variables for the affective, behavioural and cognitive component of engagement were created. The variable group which represents personalization for the experimental group was coded as a dichotomous variable with the value 1 (representing the experimental group) and 0 (representing the control group). The dataset was then converted into long format and a time variable with six different time points was created (pre-intervention, day one, day two, day three, post-intervention and follow-up).

Next, descriptive statistics were applied and Pearson correlations of engagement and wellbeing were conducted for both groups to get a first impression of associations between those factors. Since the Shapiro Wilks test revealed a normal distribution for wellbeing scores but not for engagement scores, generalized linear mixed models were chosen to account for this and to answer research question one and two. The models included group, time, and the group-time interaction as fixed factors, while the subjects were treated as a random effect. The first model included wellbeing as the dependent variable, addressing the first research question. Three additional models were run with the fixed and random effects but the respective component of engagement as the outcome variable. To test for significant effects a significance level of $p = .05$ was applied.

For the mediation analysis, a mean score variable was calculated for each of the three components. This was done by building a mean from the respective component's sum scores at each measurement time point. The respective mean score variable represents the mean level of engagement for each component, ranging from day one to post-intervention, which were used as the three mediator variables (Figure 4). The mediation analysis was conducted with the PROCESS macro tool v. 4.1 for SPSS (Hayes, 2022). To account for not normally distributed engagement scores, the non-parametric method of bootstrapping with 5000 resamples was used to compute the direct and indirect effects. Significant mediation effects can be concluded if the 95 % confidence intervals of the indirect effects do not comprise the value zero.

Figure 4

Mediation analysis of the effect of personalization (group) on wellbeing through the mediators affective, behavioural and cognitive component of engagement



Results

Descriptive statistics

The final data set included 230 participants with a mean age of 20.47 (*SD* = 1.90). Independent samples *t*-tests revealed no significant differences between the control group and experimental group for the variables gender ($t(228) = -0.43$, $p = .668$), age ($t(228) = -1.32$, $p = .187$) and nationality ($t(228) = -0.87$, $p = .383$). Demographics for both groups are shown in Table 2.

Table 2

Sample demographics of the control and experimental group (n = 230)

		Control group		**Experimental group**		**Total**	
Variable	**Category**	***n***	**%**	***n***	**%**	***n***	**%**
Participants		113	49.1	117	50.9	230	100
Gender	Female	80	34.8	83	36.1	163	70.9
	Male	33	14.3	33	14.3	66	28.6
	Prefer not to say	-	-	1	0.4	1	0.4

Age	18 - 21	91	39.6	85	37.0	176	76.6
	22 - 25	20	8.7	30	13.0	50	21.7
	26 - 31	2	0.9	2	0.9	4	1.8
Nationality	German	60	26.1	71	30.9	131	57.0
	Dutch	32	13.9	26	11.3	58	25.2
	Other	21	9.1	20	8.7	41	17.8

Wellbeing and Engagement

On a scale from 14 to 84, the overall mean scores of wellbeing were 51.93 (*min* = 21, *max* = 75, *SD* = 11.00) at pre-intervention, 55.4 (*min* = 17, *max* = 80, *SD* = 11.72) at post-intervention and 54.39 (*min* = 24, *max* = 82, *SD* = 12.43) at follow-up. Paired samples *t*-tests showed a significant increase from pre- to post-intervention $t(198) = -5.40$, $p < 0.001$ and an insignificant decrease from post-intervention to follow-up $t(106) = - 0.68$, $p = .500$.
Mean wellbeing scores per group can be seen in Table 3. It shows that pre-intervention wellbeing scores are already higher in the experimental group (52.48 vs 51.37), however a two-sample T-test revealed this difference not to be significant, $t(228) = -.762$, $p = .447$. The results thus indicate a general increase in wellbeing from pre- to post intervention for both groups which can also be observed at the follow-up measurement five weeks later with only slight decreases (Figure 5).

Results of the TWEETS showed that on a scale from 0 to 36, scores were distributed as follows: scores on day one ranged from 9 to 36 (*M* = 25.10, *SD* = 4.22), scores on day three ranged from 6 to 36 (*M* = 23.62, *SD* = 5.46), scores on day seven ranged from 4 to 36 (*M* = 23.46, *SD* = 5.80) and scores at post intervention ranged from 0 to 36 (*M* = 22.07, *SD* = 6.66). Table 3 shows the mean scores of the affective, behavioural and cognitive component of engagement at each time point for both groups. These scores indicate a slight continues decrease in engagement from day one up until post intervention which Figure 6 illustrates.

Table 3

Mean Wellbeing and Engagement scores of the control and experimental group

	Control group		Experimental group	
	M	*SD*	*M*	*SD*
Pre-intervention Wellbeing	51.37	1.03	52.48	1.02
Post-intervention Wellbeing	54.13	1.21	56.52	1.14
Follow-up Wellbeing	53.40	1.85	55.24	1.55
Day 1 Engagement	24.71	4.37	25.52	4.05
Affective	8.08	1.85	8.55	1.71
Behavioural	8.22	1.73	8.29	1.71
Cognitive	8.41	1.57	8.70	1.53
Day 3 Engagement	23.44	5.78	23.80	5.15
Affective	7.64	2.27	7.86	1.99
Behavioural	7.79	2.01	7.79	1.94
Cognitive	7.97	2.13	8.15	2.08
Day 7 Engagement	23.48	5.85	23.44	5.77
Affective	7.54	2.31	7.48	2.30
Behavioural	7.73	2.11	7.78	2.17
Cognitive	8.16	2.03	8.19	2.08
Post-intervention Engagement	21.99	7.05	22.13	6.34
Affective	6.76	2.80	7.18	2.54
Behavioural	7.38	2.46	7.38	2.27
Cognitive	7.84	2.53	7.58	2.55

Figure 5

Mean wellbeing scores per group

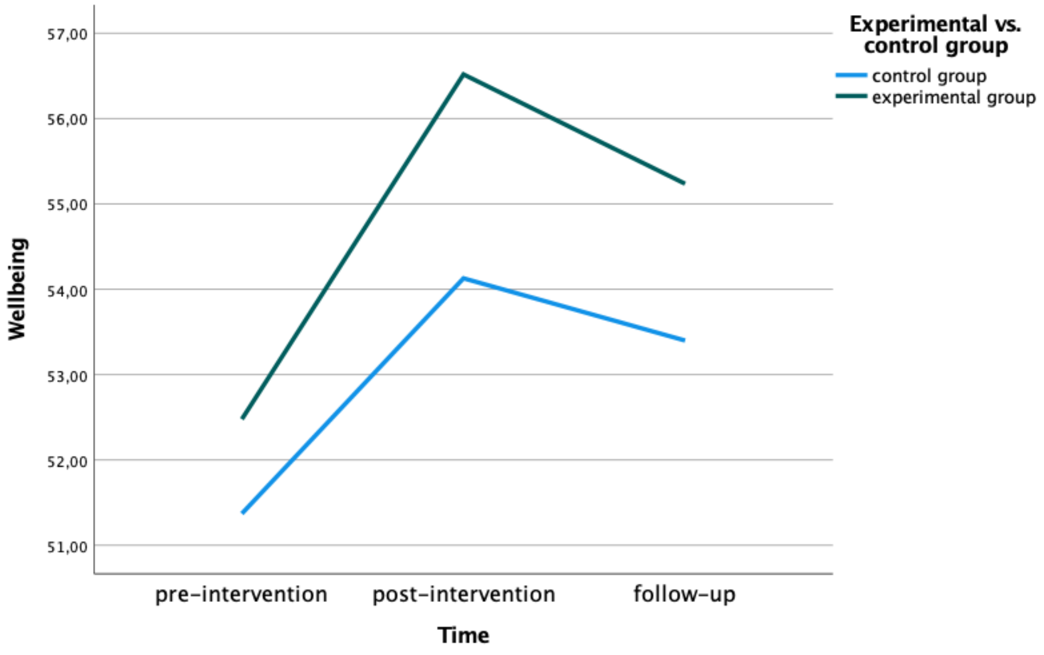
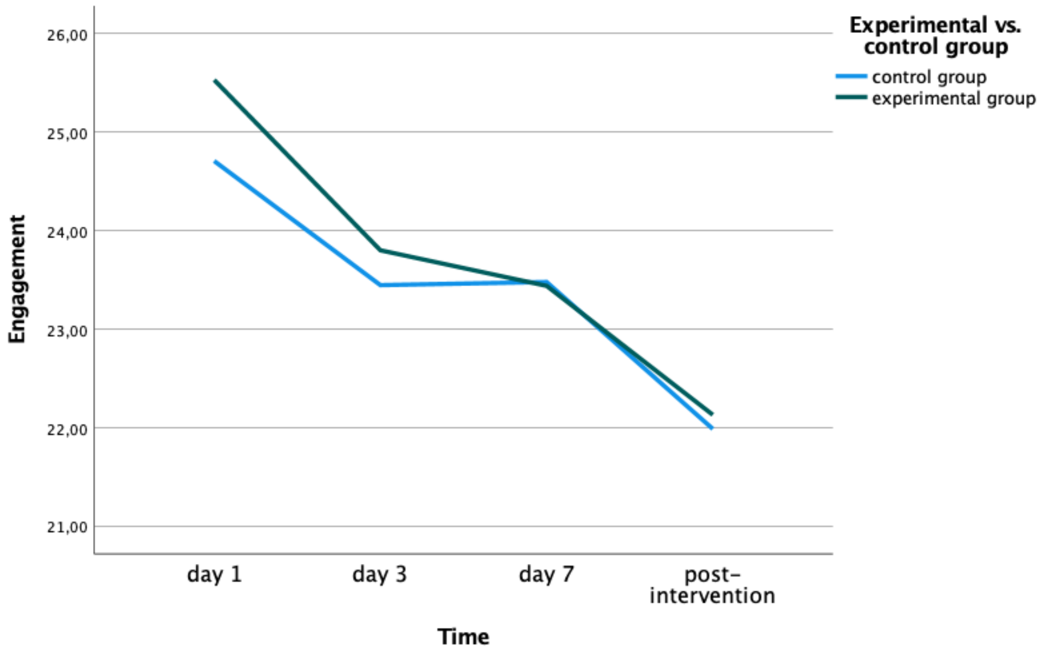


Figure 6

Mean engagement scores per group



Pearson correlations

Pearson correlations of wellbeing and engagement measures for both groups are shown in Table 4. For the experimental group, engagement measures from day one (r = .34, p

< .001) to post-intervention (*r* = .38, *p* < .001) were positively associated with post-intervention wellbeing at a significant level. For the control group this was only the case for day 3 engagement (r = .26, *p* = .021). This indicates that wellbeing might increase with higher levels of engagement in a personalized intervention which will be further analysed in the following models.

Table 4

Pearson correlations of wellbeing and engagement measures

		T_0 Wellbeing	Day 1 Engagement	Day 3 Engagement	Day 7 Engagement	T_1 Engagement	T_1 Wellbeing	T_2 Wellbeing
Control group	T_0 Wellbeing	1						
	Day 1 Engagement	.12	1					
	Day 3 Engagement	.10	.75**	1				
	Day 7 Engagement	.05	.63**	.75**	1			
	T_1 Engagement	.18	.63**	.74	.85**	1		
	T_1 Wellbeing	.63**	.14	.26*	.13	.19	1	
	T_2 Wellbeing	.52**	.12	.14	.00	.16	.71**	1
Experimental group	T_0 Wellbeing	1						
	Day 1 Engagement	.22*	1					
	Day 3 Engagement	.15	.68**	1				
	Day 7 Engagement	.22*	.61**	.69**	1			
	T_1 Engagement	.17	.48**	.57**	.66**	1		
	T_1 Wellbeing	.64**	.34**	.28**	.25*	.38**	1	
	T_2 Wellbeing	.57**	.19	.02	.05	.11	.72**	1

Note. "**" means that correlation is significant at the .001 level. "*" means that correlation is significant on the .05 level.

Linear mixed effects modelling analyses

Results of the linear mixed effects modelling analyses showed that a significant main effect of time $F(2, 532) = 15.36$, $p < .001$, on wellbeing was found. Personalization (group) $F(2, 532) = 1.00$, $p = .317$, and the interaction of personalization (group) and time $F(2, 532) = 0.19$, $p = .830$, were not found to be significant. This indicates that a personalized intervention compared to a control condition has no significant effect on mental wellbeing over time. In addition, significant main effects of time on the affective $F(3, 749) = 27.31$, $p < .001$, behavioural $F(3, 749) = 9.77$, $p < .001$ and cognitive component of engagement $F(3, 749) = 11.41$, $p < .001$ were found. However, no significant effects of personalization (group) were found on the affective $F(1, 749) = 1.38$, $p = .240$, behavioural $F(1, 749) = .03$, $p = .872$ and cognitive component $F(1, 749) = .27$, $p = .604$. Interaction of personalization (group) and time also had no significant effect on the affective $F(3, 749) = .57$, $p = .636$, behavioural $F(3, 749) = .15$, $p = .932$ and cognitive component $F(3, 749) = 1.65$, $p = .177$. The results thus indicate that personalization has no significant effect on the three components of engagement.

Mediation analysis

The mediation analyses showed no significant effects of the predictor personalization (group) on the mediators affective ($p = .382$), behavioural ($p = .831$) and cognitive component of engagement ($p = .848$) (*a*-paths; Table 5; Figure 7). On the *b*-paths, the affective ($p = .978$) and cognitive component ($p = .865$) showed no significant effects on wellbeing. Only the behavioural component had a significant effect on wellbeing, $p = .037$. In addition, the direct effect ($p = .511$) and total effect ($p = .479$) of personalization (group) on wellbeing were not significant. Bootstrap confidence intervals of the indirect effects all comprised the value zero. Thus, the results indicate that the three components of engagement do not mediate the effect of personalization on wellbeing nor that there is a significant effect of personalization on wellbeing.

Table 5

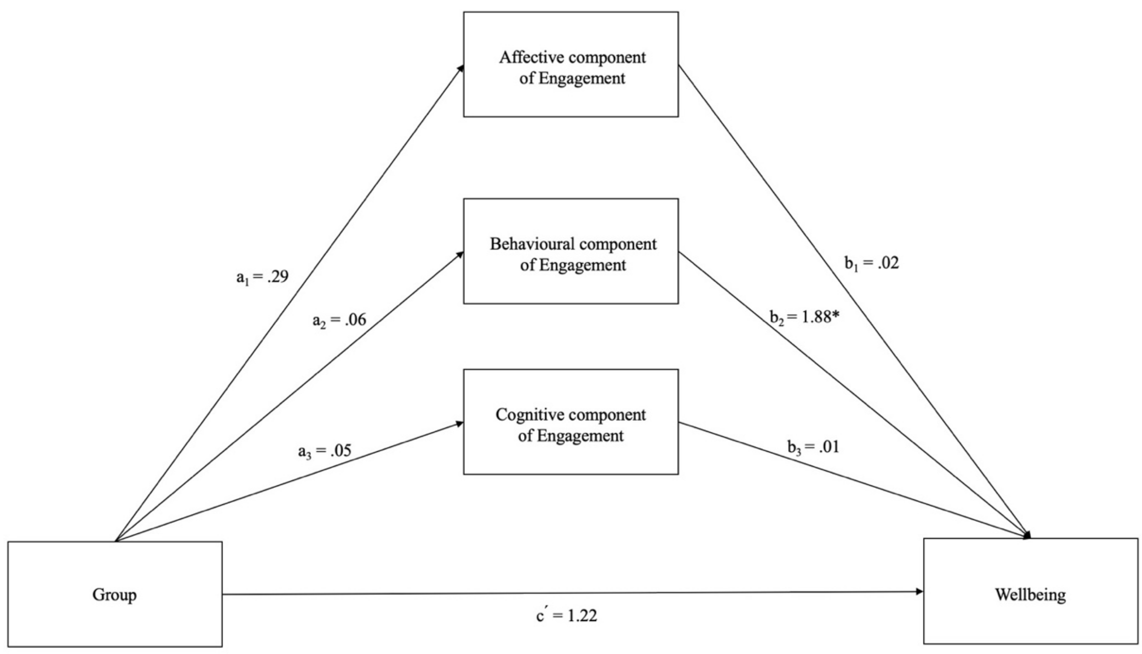
Mediation analysis of the effect of personalization (group) on wellbeing through the mediators affective, behavioural and cognitive component of engagement

Predictor	Mediator	*a*	*b*	*a x b* (Indirect Effect) (95% C.I.)[a]	*c* (Total Effect)	Direct Effect
Group	Affective component	.29	.02	.01 (-1.26, 1.17)	1.34	1.22
	Behavioural component	.06	1.88*	.12 (-1.05, 1.44)		
	Cognitive component	.05	.17	.01 (-.78, 78)		

Note. * $p < .05$. [a] Bootstrap confidence intervals are bias corrected (5000 resamples).

Figure 7

Mediation analysis of the effect of personalization (group) on wellbeing through the mediators affective, behavioural and cognitive component of engagement



Note. * $p < .05$

Discussion

Main findings

The purpose of this study was to investigate the effect of engagement in a wellbeing DHI for students. Specifically, the study examined whether personalization of the intervention influenced the affective, behavioural, and cognitive component of engagement, as well as wellbeing outcomes. However, no effects of personalization on these variables were found. This means that whether a participant received a version of the intervention that matched his or her preferences did not significantly influence the effectiveness of the intervention nor how engaged participants were. Moreover, the study investigated the potential mediating effect of the three components of engagement in the relationship between personalization and wellbeing outcomes but did not yield any mediating effects. Surprisingly though, the behavioural component was the only one which had a significant effect on wellbeing. In addition to these findings, a small but significant improvement in wellbeing was found in both groups regardless of personalization while a continuous decline of engagement over the course of the intervention was found for both groups.

Interpretation and implications

The non-significant effects of personalization are in contrast to prior research that found personalization to have a positive effect on both engagement and effectiveness of interventions (Hollis et al., 2017; Burley et al., 2020; Jahedi et al., 2022; Lustria et al., 2013; Moe-Byrne et al., 2022). Therefore, it might be assumed that the underlying personalization procedure in the current study was neither effective to promote wellbeing nor engagement since content, feedback and design may have not been adjusted the participants' needs. While Hyland & Whalley's (2008) findings stress that it is important to consider personal values and beliefs for choosing the content of an intervention, it is conceivable that showing participants different options only before the intervention is not optimal to find the best working version for each participant. A short description of the content might just not be sufficient to ensure a good match with participants' values and beliefs. What could be done instead is to fit the type of content, design and feedback to participants' preferences in real-time after a module has been finished because experiencing an intervention might result in a more valid preference than indicating one's preference before knowing how one experiences the intervention. This would be in line with other research that stresses the importance of co-design and user feedback (Pelletier et al., 2022) and an adaptive personalization strategy of psychological interventions (Jahedi et al., 2022). Moreover, this would then result in not one fixed static version of an intervention but a dynamic change of options throughout the intervention. Furthermore, Jahedi et al. (2022) mention that artificial intelligence could help with such a dynamic personalization of digital interventions. One concrete example of this is the way feedback can be delivered. In the current study personalization was only applied to the way feedback was given but not to the content of the feedback. Artificial intelligence chatbots, however, could give the users personalized feedback based on their input (Boucher et al., 2021), which might result in a more meaningful response for the individual user and higher engagement.

Non-significant effects of personalization may also be attributed to the factor design and the lack of a working gamification as part of the design, since those participants who preferred the competitive or non-competitive design choice over the non-gamified option might not have benefitted much from this feature for two reasons. Firstly, it can be argued that showing cartoon pictures of a cyclist's journey to indicate progress in the intervention might hardly be counted as a gamification element. Secondly, even though the competitive design displayed the pile of bricks and the amount next to it which indicates a kind of measurable progress in the intervention, the use of other gamification elements could have led to a higher engagement. Although participants set goals at the beginning of the intervention, which can be an effective gamification element (Xu et al., 2022), other gamification elements were not made use of, such as challenges, badges, rewards, competition, collaboration or a storyline (Xu et al., 2022). However, applying any of these elements to a wellbeing intervention might per se not lead to higher engagement or effectiveness since the context and aim of the intervention must be taken into consideration (Hamari et al., 2014). For a wellbeing DHI like the current one which only offers a very limited gamification it should therefore be tested which of these elements actually do make a difference.

Subsequently, the significant effect of the behavioural component of engagement and the non-significant effects of the other two components need to be discussed since these findings seem to be contrary to the conceptualization of engagement by Kelders et al. (2020a) which went away from only being a behavioural one and incorporates cognitions and affect as well. A possible explanation for this might lie in the continuous decline of engagement as a whole over the course of the intervention. As Kelders and Kip (2019) found in their development of the TWEETS, being behaviourally engaged in a technology is reflected by building an effortless and easy to use routine of using the technology. It might be that the daily participation in the intervention was just that for most participants, a built-up routine with no significant positive cognitions and emotions attached to it, hence no significant effect of the cognitive and affective component on wellbeing outcomes. This might be because the incentive for participating students may have been more towards earning credit points instead of wanting to improve wellbeing.

Another aspect that needs to be considered is the construct of the target variable that may or may not be influenced by the three components. Previous research found engagement to be this multidimensional construct (Kelders, 2019; Kelders et al. 2020a) and advised to measure it in interventions that investigate engagement (Bijkerk et al., 2023). However, to the researcher's knowledge, no research has been conducted yet that compared the influence of engagement's components on different outcome measures, but only the influence of engagement as a whole. This might also be because conceptualizing and measuring different components of engagement is a relatively new approach. The significant influence of the behavioural component on wellbeing in the current intervention should thus not necessarily be assumed to be found when investigating the influence of engagement on other psychological constructs such as anxiety or depression.

Lastly, even though the current study did not reveal any significant effects of personalization on engagement's components and wellbeing, the intervention per se proved to be effective in increasing wellbeing, despite a decline of engagement over time. While this effect might be small it was still found to be significant even five weeks after the end of the intervention. This should be regarded as a success considering the relatively low effort participants had to invest daily. Therefore, the findings of the current study still serve to emphasize that a wellbeing DHI can be scalable and effective at the same time which previous research also found (Murray et al., 2016, van Agteren et al., 2021).

Strengths and limitations

Among the strengths of the study is the fact that a randomised controlled trial was applied to assign participants to either the experimental group or the control group. This would ensure to attribute the effects on engagement and wellbeing outcomes to the indicated preferences of design, feedback and content if such an effect had been found and not on other confounding factors such as participants' demographics. Another strength is that within the personalization procedure different factors have been tailored to the participants preferences. This can be counted as a strength, considering that personalized DHIs often only focus on one dimension of the intervention, as Hornstein et al. (2023) found. Furthermore, measuring engagement at different time points allowed to get a better understanding of its changing nature instead of relying on only one static measurement. Lastly, using the TWEETS, a reliable scale with good psychometric properties, in this study, allowed to gain initial insights into the role of the different components of engagement since it is the first valid scale that effectively measures engagement with eHealth technologies, taking these components into account.

Among the limitations of the current study is that the findings may not be generalized to a larger population since the sample demographics are relatively homogenous, only consisting of university students, which were predominantly female and around the age of twenty years. Moreover, participants' motivation to partake and earn credit points may have influenced the quality and strength of the different components of engagement, which was not assessed. Since motivation and engagement can influence each other (Martin et al., 2017) it is conceivable that an external incentive such as earning credit points by participating might have a different effect on engagement than an intrinsic motivation such as the intention to improve one's wellbeing. This is because participants could be engaged in a more meaningful way if they really want to improve their wellbeing which then goes beyond a mere routinely behaviour (Graffigna & Barello, 2018). Therefore, it might be assumed that the associated positive emotions and cognitions with a meaningful intervention could be reflected in the quality of engagement and result in a stronger affective and cognitive component.

Another limitation is that in the current study engagement was only viewed as a process over time while it can also be viewed as a state (Sonnentag, 2017). This is important, considering that some modules had to be carried out through the course of a day and could only be reflected upon later in the app, hence no assessment of engagement in the moment was applied. In their integrative review of methods to measure engagement with mental health and behaviour change interventions, Bijkerk et al. (2023) mention multiple methods of assessing engagement in interventions, such as self-report questionnaires like the TWEETS, observer-report questionnaires and ecological momentary assessments. Especially applying ecological momentary assessment could provide a more comprehensive picture of engagement, particularly also for those intervention modules that stretch over a whole day. Combining measurements such as the TWEETS with ecological momentary assessment may therefore result in a more comprehensive understanding of engagement, its fluctuations and how it develops over time.

Future research

From the given findings, literature and limitations, the following practical and theoretical recommendations can thus be derived: future research should focus on optimizing and applying an adaptive personalization strategy for DHIs to improve engagement and effectiveness, also through the use of artificial intelligence and machine learning. Moreover, within the personalization procedure it should further be investigated which gamification elements actually make a difference in wellbeing DHIs.

Since previous research found engagement to be an important factor for the effectiveness of DHIs and the current study looked at it only in the context of wellbeing, it is advised to further investigate the role of the different components of engagement regarding other outcome variables to find out how they are influenced affectively, behaviourally and cognitively. Lastly, future research should also investigate the role of participants' initial motivation to take part in an intervention through a questionnaire prior to an intervention since intrinsic and extrinsic incentives might influence their level and quality of engagement, meaning which component may be more pronounced.

Conclusion

In conclusion, the findings of the current study underscore the importance of implementing personalized and dynamic procedures to effectively enhance engagement and effectiveness in DHIs. While the study demonstrated the efficacy of a DHI in improving mental wellbeing, the continuous decline in engagement highlights the need to discover methods for sustaining high engagement levels throughout the intervention. Furthermore, the unexpected effect of behavioural engagement on intervention effectiveness raises questions about the role of initial motivation in this context and how different components of engagement influence outcomes beyond wellbeing.

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Appendices

Appendix A

MHC-SF (Keyes, 2002)

During the past month, how often did you feel:	Never	Once or twice	About once a week	About 2 or 3 times a week	Almost every day	Every day
...happy?	❑	❑	❑	❑	❑	❑
...interested in life?	❑	❑	❑	❑	❑	❑
...satisfied with life?	❑	❑	❑	❑	❑	❑
...that you had something important to contribute to society?	❑	❑	❑	❑	❑	❑
...that you belonged to a community (like a social group, or your neighborhood)?	❑	❑	❑	❑	❑	❑
... that our society is a good place, or is becoming a better place, for all people?	❑	❑	❑	❑	❑	❑
...that people are basically good?	❑	❑	❑	❑	❑	❑
...that the way our society works makes sense to you?	❑	❑	❑	❑	❑	❑
...that you liked most parts of your personality?	❑	❑	❑	❑	❑	❑
...good at managing the responsibilities of your daily life?	❑	❑	❑	❑	❑	❑
... that you had warm and trusting relationships with others?	❑	❑	❑	❑	❑	❑
...that you had experiences that challenged you to grow and become a better person?	❑	❑	❑	❑	❑	❑
...confident to think or express your own ideas and opinions?	❑	❑	❑	❑	❑	❑
... that your life has a sense of direction or meaning to it?	❑	❑	❑	❑	❑	❑

Appendix B

Modified TWEETS items for evaluating engagement scores at post-intervention

Item	TWEETS post measurement item
1	Using this app did become part of my daily routine
2	The app took me little effort to use
3	I was able to use the app as often as needed (to achieve my goals)
4	This app made it easier for me to work on increasing my wellbeing
5	This app motivated me to increase my wellbeing
6	This app helped me to get more insight into my wellbeing
7	I enjoyed using this app
8	I enjoyed seeing the progress I made in this app
9	This app fits me as a person

Appendix C

The TWEETS from Kelders et al. (2020b)

Table 1. 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."