User Engagement and Wellbeing: The Role of Digital Self-Monitoring in Mental Health Support

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Abstract

Growing global concerns around mental health require innovative and adaptive solutions. Technological support tools such as web applications provide an opportunity for such innovation, but even the most efficacious platform is limited by its ability to promote user engagement. This study explored the impact of user engagement in technology-supported self-monitoring for wellbeing in a cohort (N=196) of university undergraduate students. We aimed to identify an efficient measurement model for daily wellbeing, examining the impact of optimizing user-centered design to promote engagement and enhance user experience. To this end, participants were randomly assigned to either a passive control condition or to one of two daily self-reflection conditions. Self-reflection prompts were delivered using either an online questionnaire platform (Qualtrics), or an app designed specifically to engage users in wellbeing reflection (UpBeing). Results indicated that including general appraisal items alongside momentary affect assessment improved model fit compared to affect measurement alone. Furthermore, wellbeing-centered design (UpBeing) significantly enhanced self-reported wellbeing compared to both Qualtrics and the control conditions, accompanied by decreased negative mood and improved decentering skills. These findings suggest that app-based self-reflection tools like UpBeing can effectively support individuals' wellbeing and coping abilities in daily life. Analysis of user experience reports suggested that the design of the UpBeing app likely contributed to its superior performance. Given that many apps only measure affect/mood without general appraisals of wellbeing, the study highlights the importance of validating measurements models in wellbeing support tools. While research into longitudinal and clinical outcomes is needed, implementing user-centered design in mental health support tools may be a promising method for enhancing health benefits through increased user engagement.

Keywords: digital mental health, mobile health applications, self-monitoring tools, user engagement, wellbeing measurement

Introduction

Promoting wellbeing and mental health is increasingly seen as an essential social priority (Singh et al., 2022), with broad implications for human flourishing, social cohesion, and economic productivity (Cooper, 2010; VanderWeele et al., 2020). Wellbeing promotion is particularly important in post-secondary education, where academic demands, adapting to independent living, the need to establish new social support systems, and financial uncertainty can all significantly tax psychological resources (Acharya et al., 2018). Unresolved stress has negative consequences across life domains, sapping motivation, cognitive function, emotion regulation, and the quality of sleep and diet; this deterioration then increases the risk of burnout, strains relationships, compromises physical health, and erodes life satisfaction (Cohen et al., 2019; Hall et al., 2016; Roberson et al., 2018). Conversely, achieving and maintaining positive wellbeing has been robustly linked to heightened creativity, productivity, interpersonal rapport, resilience, and thriving across personal and professional spheres (Henriksen et al., 2020; Lyubomirsky et al., 2005; Miller, 2016; Wang & Wong, 2014). Post-secondary wellness initiatives appear to be efficacious (Dawson et al., 2020; Winzer et al., 2018), but constraints on institutional resource often limit access and availability. This unmet need underscores an urgency to foster innovative, scalable approaches for proactive self-monitoring and self-directed management of wellbeing - especially for vulnerable populations like post-secondary students.

Wellbeing is a multidimensional construct encompassing mental, physical, and social domains integral to human flourishing (Ruggeri et al., 2020). It is inherently complex, ranging from the fulfillment of basic physiological needs to aspirations towards self-actualization and self-transcendence (Maslow, 1943). Proposed models emphasize the quality of subjective experiences (Diener et al., 2018), environmental mastery (Burns, 2005), relationships (Demir et al., 2007), value fulfillment (Rajani et al., 2019), socioeconomic status and financial security (Netemeyer et al., 2018), among other elements.

With such diverse life domains to be addressed, there is no consensus on how best to empower self-directed wellbeing promotion. One option may be to work with transient or ‘state’ wellbeing, with the idea that scaffolding momentary self-reflection could lead to long term growth. Mobile health applications offer numerous advantages over conventional modalities, including negligible costs, high scalability, and privacy, encouraging use without the fear of stigma (Linardon et al., 2019). Research has shown that technology can play a pivotal role in fostering self-regulation and promoting wellbeing. For instance, digital platforms can provide real-time feedback and personalized interventions, enabling individuals to monitor and manage their mental health effectively (Morris et al., 2010). Additionally, mobile health applications can facilitate the development of self-regulatory skills by offering tailored strategies and tools for stress management and emotional regulation (Heron & Smyth, 2010). These capabilities can enhance users’ ability to maintain a balanced emotional state, contributing to long-term psychological wellbeing (Baños et al., 2017). Initial evidence in post-secondary samples suggests that brief, technology-supported self-care reflection acts as a buffer against stress and negative affect in post-secondary samples (Fiodorova & Farb, 2021). However, it appears to be specifically the ability to promote inertia, or stability, of positive affect at the state level that most powerfully predicts greater long-term wellbeing up to a year later (Mitchell et al., 2024). In post-secondary contexts, if technology can help support the maintenance of daily positive affect, these practices could yield lasting improvements in wellbeing during this formative period.

User Engagement in Technology-Supported Wellbeing Promotion

Optimism over mobile mental health technology must be tempered by the practical question of user engagement. Many users only use an app a few times, with Yang et al. (2020) suggesting that 26% of health app users only use an app once after downloading, and a 74% attrition rate within the first ten uses. Such ‘doses’ are likely far below the evidence base on which an intervention has been validated; for example, Mindfulness-Based Stress Reduction has well-validated positive effects in community samples (Querstret et al., 2020), but requires 8 weekly classes, daily homework exercises, and an (optional) full-day group session. Comparable interventions aimed at promoting flourishing in post-secondary student populations have similar (30 hour+) time requirements (Seppälä et al., 2020). Unless apps are miraculously more efficient and effective than gold-standard approaches such as group wellness interventions; to even approximate this treatment dose, an app would have to be used regularly for much longer than a handful of sessions.

Optimistically, apps may indeed provide some efficiency gains by customizing content towards users’ needs and preferences and have the potential for providing longitudinal support with fewer barriers to practices. Yet for local app benefits to develop into long-term wellbeing promotion, user engagement is critical, specifically the cultivation of intrinsic motivation and emotional investment in a digital tool or process (Linardon et al., 2019; Peters et al., 2018). Higher engagement predicts better adherence, heightened satisfaction with digital interventions, and significant improvements in outcomes such as stress reduction and overall flourishing (Jayawardene et al., 2017; Ryan et al., 2019).

The Search for Parsimony in Longitudinal Wellbeing Assessment

Developing psychometrically sound assessments is crucial for effective research and interventions, but this requires balancing comprehensiveness with practicality, especially for longitudinal studies tracking individual changes over time (VanderWeele et al., 2020). Due to its complex and multifaceted nature (Maslow, 1943), there seems to be little agreement on the core components of wellbeing, with no standardized measurement model and a variety of popular instruments being used (Upsher et al., 2022). Creating a reliable, brief wellbeing measurement model for daily use is therefore critical for app success, as more conventional, longform questionnaires are unlikely to sustain user engagement given the state of the app marketplace described above.

One major departure from the research literature for the sake of efficiency is that many apps appear to eschew broad appraisals of wellbeing such as general life satisfaction in their daily check-in process. This is unusual given an abundance of research suggesting that a minimal characterization of wellbeing rests on a tripartite structure consisting of positive affect, negative affect, and life satisfaction appraisals (Adler & Fagley, 2005; Busseri & Sadava, 2011; Diener, 1984; Diener et al., 2003; Emmons & Diener, 1985; Oishi et al., 2007; Sagiv & Schwartz, 2000). Various models have been proposed to explain the relationships among these three components (Busseri & Sadava, 2011; Kozma et al., 1990; Schimmack et al., 2002). However, given their correlated structure, it remains unclear how to most efficiently capture all three components over the type of brief, repeated measurements required in longitudinal, high-resolution wellbeing research. It remains unknown whether wellbeing can be adequately represented through arousal-valence (energetic/calmness and positive/negative affect) assessments alone, or if explicitly prompting a separate appraisal of one's overall current state provides incrementally valid wellbeing prediction and personalization.

Designing for User Engagement

Strategies for promoting deep engagement include personalization based on user preferences, interactive features that empower users, and machine learning-content to meet personal and contextual needs (Carroll et al., 2017; Mohr et al., 2014). Research indicates that personalization can cultivate a sense of ownership and relevance among users, leading to higher completion rates and enhanced outcomes (Yardley et al., 2016). Leading apps go beyond tracking symptoms to encourage mindful self-reflection and positive experience appreciation through features like gratitude journaling (Seligman et al., 2006; Shah et al., 2022). However, maintaining engagement requires more than just meaningful activities; it necessitates a user experience that is both aesthetically pleasing and functionally rewarding, encouraging feelings of competence and enjoyment (Beckmann et al., 2022; Hassenzahl et al., 2010; Lavie & Tractinsky, 2004).

This necessity for engaging user experiences accords with the opportunities presented by technological innovations in wellbeing monitoring and support. Incorporating technologies like real-time data analysis and ecological momentary assessment, these apps respond to users' changing needs dynamically (Torous et al., 2021). Existing apps have demonstrated the efficacy of multidimensional self-tracking by combining passive data (e.g., weather and activity levels) with active user input to offer a holistic view wellbeing (Oakley-Girvan et al., 2021; Parry et al., 2023). Such apps show promise for empowering individuals to take a self-guided, data-driven approach to their unique wellbeing journeys and flourishing.

Current Research Objectives

While app-based, self-guided approaches hold promise for enhancing the accessibility and personalization of wellbeing tracking, research is needed to refine their deployment and maximize their efficacy. The literature on the effectiveness of mobile app-based wellbeing monitoring and sustaining user engagement over extended periods is limited (Baumel et al., 2019; Szinay et al., 2020). Additionally, there is a lack of consensus on the most effective user engagement strategies and the design of superior user experiences, highlighting the need for iterative, user-centric design approaches (Brouwer et al., 2011; Hassenzahl et al., 2010; Saleem et al., 2021). Concurrently, the debate over optimal approaches for capturing the complex dimensions of wellbeing through self-report measures continues, especially within the context of integrating passive data from mobile sensors and user interaction patterns, which further complicates wellbeing assessments (Woodward et al., 2022).

The present research investigates how designing for user engagement impacts mental health outcomes in the context of technology-supported self-monitoring and self-care promotion. The study features a collaboration between academic researchers and UpBeing Inc. a start-up app company in the mobile health field, leveraging the company's investment in designing for user engagement as a comparator to the more 'bare bones' approach that is often used in academic research.

The study had two aims. First, we sought to investigate the most parsimonious measurement model for daily wellbeing, focusing specifically on whether broader appraisals of life satisfaction improve model fit beyond the capture of momentary positive and negative affect. Second, we investigated the impact of optimizing user-centered design to promote engagement, examining whether using the UpBeing app yields higher quality self-report responses and an enhanced user experience compared to conventional online survey platforms like the Qualtrics survey platform. Qualtrics was chosen because it has been widely employed by research studies and is considered a representative of modern survey software, with the ability to implement various studies and administer a range of procedures, from questionnaires to randomized experiments (Carpenter et al., 2019). Through a mixed-methods exploration of these questions, we aimed to generate actionable insights to inform the development of mobile applications for personalized, self-directed wellbeing monitoring.

Methods

Design

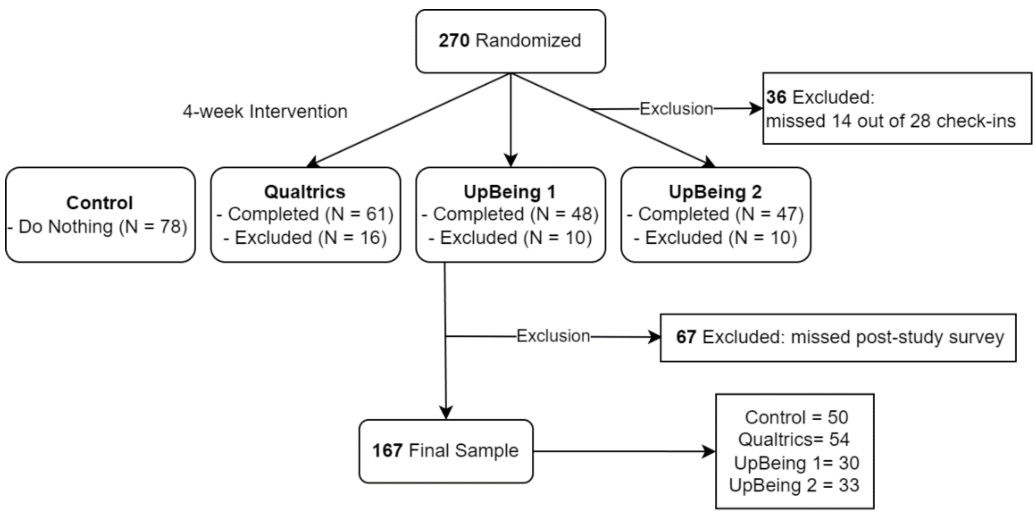
The study employed a mixed-model, multilevel clinical trial design with four groups to investigate the potential benefits of daily check-ins and compare the effectiveness of two platforms: the advanced UpBeing mobile app versus the traditional Qualtrics platform. Participants underwent online assessments at baseline and post-intervention stages, attending up to 28 daily sessions over four weeks. All scales and analyses were pre-registered prior to data collection (https://osf.io/hxdvf).

Participants

Participants were undergraduate students recruited from the University of Toronto Mississauga in Fall 2023 via an online participant pool. As compensation, students could obtain up to 3% course credit toward their final grade. The research protocol was approved by the University Research Ethics Board and is consistent with the World Medical Association Declaration of Helsinki. The sample consisted of 196 participants with a median age of 18.0 years (range: 16-23). The majority (81%) identified their gender as women, while 16% identified as men. UTM is a research-intensive Canadian university with an ethnically diverse student population (20% South Asian, 19% East Asian, 16% White, 10% Middle Eastern, 9% Southeast Asian, 6% Bi-racial, 5% African, 5% Caribbean, 4% Hispanic, 3% listed as Other, and 3% preferred not to answer).

A priori power analysis was conducted before study enrollment to determine appropriate sample size. Simulations were performed in R using the 'lavaan' package for structural equation modeling (Rosseel et al., 2017) and the 'semPower' package (Moshagen, 2018). Required power was set at .956 for each of the 5 models for familywise power = .80, holding the alpha (p-value) criteria ≤ .05 and requiring RMSEA ≤ .05. The simulation suggested a required sample size of 129. However, to account for a conservative 30% attrition rate, 196 participants (49 in each condition) were recruited.

Figure 1. CONSORT Diagram Summarizing Participant Flow



Participant recruitment and flow through the study are summarized in a CONSORT diagram (Figure 1). Participants wishing to self-enroll were first screened via an online questionnaire using Qualtrics. Exclusion criteria were: (i) inability to commit to required study sessions, (ii) inability to communicate and follow instructions in English, or (iii) limited internet access. No students were excluded based on these criteria before informed consent.

Initially, 313 participants signed up for the study and were randomly assigned to one of the four conditions. However, 42 were not considered participants as they either withdrew or never downloaded the UpBeing app. Another 36 participants were excluded from state-level analyses for missing half of the daily check-ins, and 39 were excluded from trait-level analyses due to missing the post-study survey. Missing data were represented by the symbol ‘NA’ (not available) and were not manipulated.

Participant retention was low over the four-week intervention period, with 62% (N=167) of participants completing the study protocol. Many participants in the UpBeing conditions did not complete the post-study survey due to a platform change from UpBeing app to Qualtrics and an incorrectly configured email trigger setup. Although several participants reached out and were manually sent the survey, the additional post-study data from these UpBeing conditions were excluded to maintain consistency in the duration across conditions. Exploratory analyses incorporating these additional data revealed no significant differences.

Interventions

Control Group

This passive control group only participated in baseline and post-study assessments administered via the Qualtrics platform. No additional check-ins or interventions were provided.

Qualtrics Group

Participants in this condition completed daily check-ins through the Qualtrics platform. The check-ins included items assessing mood, motivation, productivity, and appraisal.

UpBeing Group 1

In this condition, participants completed daily check-ins using the UpBeing mobile application. The check-in items measured mood, motivation, and productivity.

UpBeing Group 2

Similar to the UpBeing 1 condition, participants in this group used the UpBeing app for daily check-ins. However, in addition to mood, motivation, and productivity, the check-ins also included items assessing appraisal.

Measures

Many of the explanatory and outcome variables in the study were operationalized as pre-registered composite measures, which were constructed using factor analysis via the 'psych' package (Revelle, 2017). For each composite variable, the adequacy of a single factor to summarize the questionnaires used was confirmed using Horn's Test of Principal Components and applied to questionnaire scores using the 'paran' package (Dinno, 2012) in R.

Trait Measures

Trait measures were assessed via self-report questionnaires administered at two time points: baseline and post-intervention.

Wellbeing. A composite measure of subjective wellbeing was calculated based on positive mood, negative mood, and life satisfaction ratings. Higher scores indicated greater levels of subjective wellbeing.

Positive Mood and Negative Mood. Participants rated the frequency of experiencing seven positive emotions (joy, contentment, compassion, pride, love, amusement, and awe) and seven negative emotions (anger, shame, worry, sadness, guilt, jealousy, and selfishness) on a 7-point Likert scale ranging from 1 (very infrequently) to 7 (very frequently).

Satisfaction with Life Scale (SWLS). The first three items from the SWLS (Diener et al., 1985) were used to measure life satisfaction, a component of subjective wellbeing. Participants rated their agreement with each item on a 7-point scale from 1 (strongly disagree) to

7 (strongly agree). These three items have been found to have superior psychometric properties compared to the other two items (Oishi, 2006).

Wellbeing Rating. Participants rated their current wellbeing on a single 7-point Likert item.

Decentering. The Metacognitive Processes of Decentering-Trait (MPoD-t; Hanley et al., 2020) was used to assess decentering, which encompasses meta-awareness, (dis)identification with internal experience, and (non)reactivity to internal experience. Participants rated items on a 7-point scale from 1 (never or very rarely) to 7 (very often or always), with higher scores indicating better decentering skills.

Reappraisal. Reappraisal was assessed using a total of 12 items from two scales: six items from the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003) Reappraisal subscale, and six items from the State Reappraisal Inventory (SRI; Ganor et al., 2018) Increase Positive subscale. Participants rated each item on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

Stress. The Perceived Stress Scale (PSS; Cohen et al., 1994), a 10-item scale assessing the intensity of stress appraisals, was used to measure stress. Participants rated their experienced stress on a scale from 1 (never) to 7 (very often).

Symptoms. The Patient Health Questionnaire (PHQ-4; Kroenke et al., 2009) was used to assess symptoms. It consists of four items measuring depression and anxiety symptoms, with higher scores indicating more severe symptomatology.

Motivation. The Basic Psychological Need Satisfaction in General (Deci & Ryan, 2000), a 21-item scale, was used to assess motivation. This scale measures the degree to which individuals experience satisfaction of their basic psychological needs for autonomy, competence, and relatedness. Participants rated each item on a scale from 1 to 7, with higher scores reflecting greater need satisfaction and, consequently, higher levels of intrinsic motivation.

Productivity. The SPACE scale (Williams, 2021), a 5-item scale assessing productivity across five domains (satisfaction, performance, activities, collaboration, and efficiency), was used to measure productivity. Each item was rated on a scale from 1 to 7, and the productivity score was derived by summing all items, with higher scores reflecting higher productivity.

Overall Experience Rating. Participants rated their overall experience with the study on a single 7-point Likert item.

In addition to the quantitative measures, several qualitative open-ended questions were included in the study:

Wellbeing Definition. Participants were asked, "What does the term 'Wellbeing' mean to you? How would you define Wellbeing?"

Stress Definition At baseline, participants were asked, "What does the term 'stress' mean to you?", and at the post-study survey, they were asked, "How does your understanding of 'stress' change?"

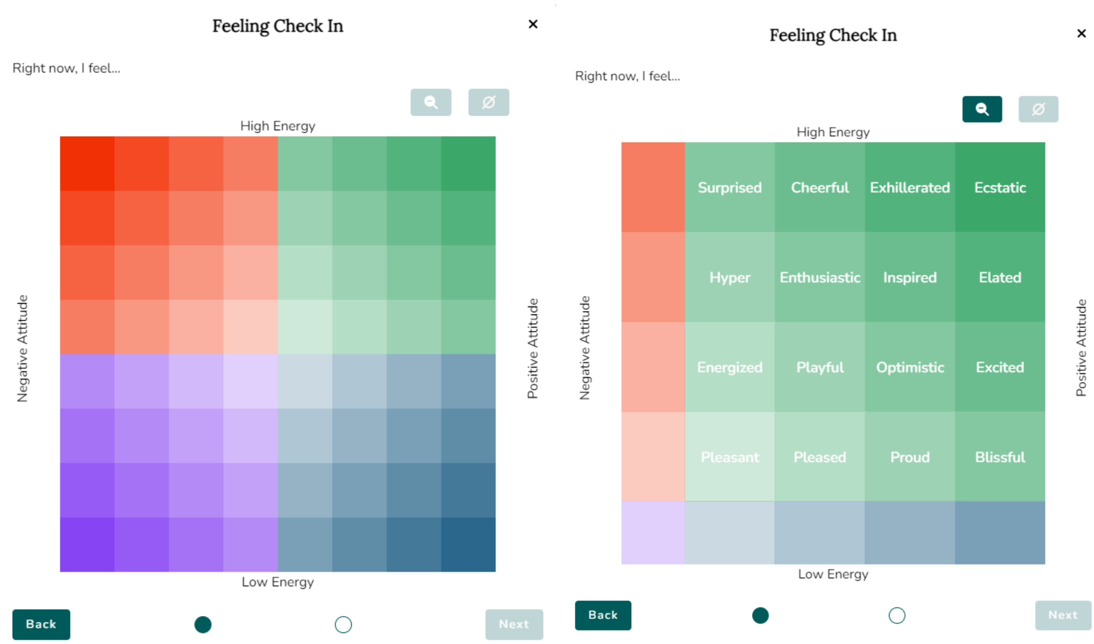
Study Expectations. At baseline, participants were asked, "What benefits (if any) do you expect to get out of this training? Do you have any concerns about doing this training?", and at the post-study survey, they were asked, "To what degree has the training met your goals and expectations?"

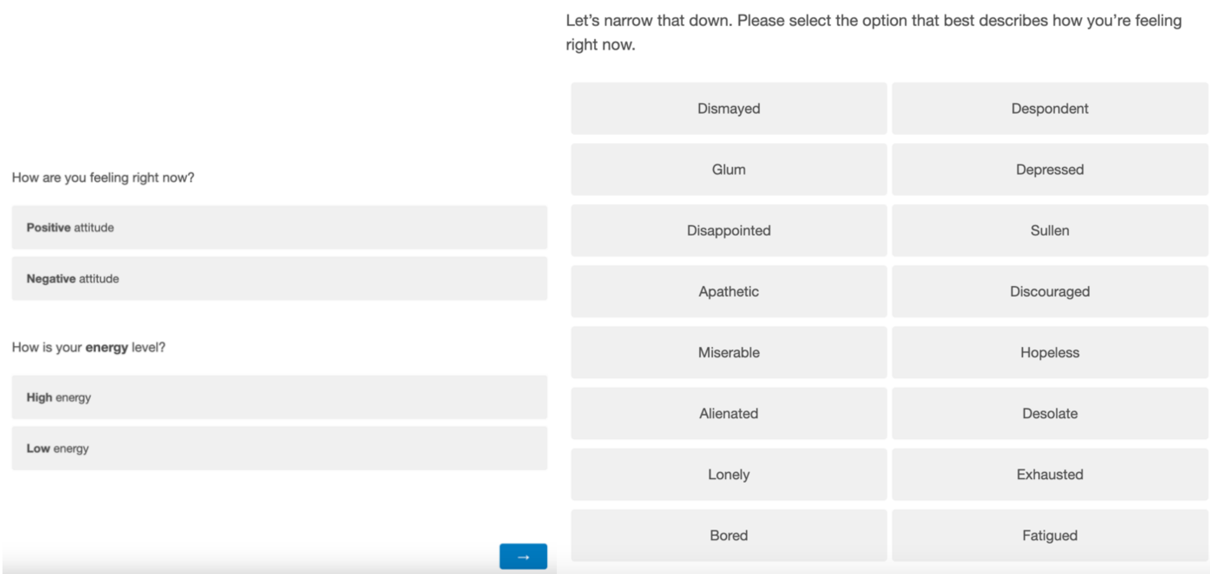
State Measures

State measures were assessed through brief daily check-ins. Mood, motivation, and productivity were measured for all intervention groups (i.e., Qualtrics, UpBeing 1, UpBeing 2), while an additional appraisal item was included only in two intervention conditions (i.e., Qualtrics and UpBeing 2). Participants were encouraged to complete check-ins twice a day. During the morning check-in (available from 12 am to 1 pm), mood and motivation were assessed. During the evening check-in (available from 1 pm to 12 am), mood, productivity, and appraisal were assessed.

Mood. Mood was assessed using a two-step mood meter (Figure 2). First, participants rated their attitude and energy levels. Based on these ratings, they were then guided to select a specific emotion word through a quadrant dial. For instance, if they selected low energy and low attitude, they were shown words like "desolate," "hopeless," and "fatigued." If they selected high energy and high attitude, they were shown words like "ecstatic," "elated," and "exhilarated." Participants were allowed to pick one emotion word.

Figure 2. The 2-Step Mood Check-in Process





Note. The top row represents the mood check-in process using the UpBeing app, while the bottom row illustrates the same process on the Qualtrics platform.

Motivation. The motivation measurement involved two steps. First, participants indicated their motivation level on a 5-point Likert scale from 1 (not motivated) to 5 (very motivated). Based on the score of this single-item motivation measure, the tone of the follow-up items was adjusted accordingly (Table 1). Participants were allowed to select more than one motivation reason.

Productivity. Similar to motivation, the productivity measure also involved two steps. First, participants indicated their productivity level on a 5-point Likert scale from 1 (not productive at all) to 5 (very productive). Based on the score of this single-item productivity measure, the tone of the follow-up items was adjusted accordingly (Table 2). Participants were allowed to select more than one productivity reason.

Appraisal. Appraisal was measured using a validated single-item Life Satisfaction Scale ("All things considered, how satisfied are you with your life as a whole?"; Lucas & Donnellan, 2011; Cheung & Lucas, 2014) on a 5-point Likert scale from 1 (very dissatisfied) to 5 (very satisfied).

Table 1. Motivation Reason Dial-down for Negative Rating and Positive Rating

Negative	Positive
I don't see value in the things I do.	I see value in the things I do.
Others don't see the value in the things I do.	Others see value in the things I do.
I don't feel equipped and competent in what I'm doing.	I feel equipped and competent in what I'm doing.
There's nothing on my to-do list I'm excited about.	I am excited about the things I do or have to do.
I don't feel connected to those around me.	I feel connected to people around me.
I struggle to see the bigger picture.	I can see the bigger picture.
It's something else.	It's something else.

Table 2. Productivity Reason Dial-down for Negative Rating and Positive Rating

Negative	Positive
I don't feel good about what I achieved today.	I feel good about what I achieved today.
The outcomes of my tasks were not successful.	The outcomes of my tasks were successful.
I didn't complete all the tasks I set out for today.	I completed all the tasks I set out for today.
I wasn't able to collaborate effectively with others.	I was able to collaborate effectively with others.
I wasn't able to stay focused on my tasks.	I was able to stay focused on my tasks.
It's something else.	It's something else.

Pre-registered Hypotheses

Hypothesis 1 posited that the incorporation of an appraisal item at the end of daily wellbeing check-ins would enhance the accuracy of wellbeing estimations. This hypothesis was based on the theoretical premise that a holistic assessment of wellbeing should extend beyond simple mood measures to encompass reflective evaluations of one's state. Hypothesis 2 aimed to assess the relationships between general reason-to-motivation and reason-to-productivity scores. Hypothesis 3 sought to determine if individual variances influenced the reason-to-motivation/productivity relationship. Hypothesis 4 aimed to compare daily mood scores across four different groups. The expectation was that the UpBeing groups would exhibit higher mood scores compared to the Control and Qualtrics groups. Lastly, Hypothesis 5 was constructed to evaluate user experience across these groups, predicting that the two UpBeing groups would demonstrate higher study ratings at the end of the study.

Data Analysis

A three-level multilevel regression model was used to analyze our results, as implemented in the "nlme" package in the R statistical programming environment (Revelle, 2017). To test for intervention effects across primary measures, a multilevel model of the interaction of conditions (Control vs. Qualtrics vs. UpBeing 1 vs. UpBeing 2) with time (baseline vs. post-intervention for the study level; 28 sessions for the daily level), controlling for participant identity with distinct ID number, was conducted. The R syntax resembled:

DV ~ Condition x Time + (1| Participant ID)

which executes the complete multilevel model:

DV ~ Nji+ 1Time, 2

j~ N0+ 1Condition + 2Condition x Time, 2, for IDj=1,…,.J

Where DV = dependent variable score for an individual observation at level 1, j indexes the participant in the sample, i indexes the individual case/score within a participant, N is the number of participants, α is the second level regression coefficient, β is the overall regression coefficient for time (fixed effect of time), γ refer to the intercept γ_0 and slopes γ_1 and γ_2 for the relationship between the predictors and the dependent variable nested within participant. The primary outcome of each test was the Condition x Time interaction.

Structural Equation Modeling (SEM) was employed for the first hypothesis. The 'lavaan' package in R (Rosseel et al., 2017) was used for the SEM analysis. To evaluate model fit, two criteria were pre-registered: the comparative fit index (CFI), and the Root Mean Square Error of Approximation (RMSEA). The target for the CFI was > .90, indicating acceptable model fit (Mueller & Hancock, 2008). An RMSEA < .10 indicates an adequate fit, and an RMSEA < .05 indicates a good fit (Mueller & Hancock, 2008).

For Hypotheses 2 and 3, comparative model analyses were conducted, assessing the predictive value of reasons on motivation and productivity. Group variances were examined through median splits and model fit enhancements. Grouping variables (e.g., high-high, low-low, high-low, low-high) were considered to test the invariance of the general model by examining whether the weights were moderated by these groups. Two tests were performed: splitting the motivation and productivity variables by median and evaluating the improvement in model fit when adding these grouping variables.

For Hypotheses 4 and 5, comparative mood and satisfaction score analyses were conducted across groups. Three tests were performed for each hypothesis to compare the mood scores and user satisfaction scores across the groups (Table 3).

Table 3. Comparison of Daily Mood Scores Across Four Groups for Hypothesis Testing

	Control	**Qualtrics**	**UpBeing 1**	**UpBeing 2**
Vs. Control	-3	1	1	1
Vs. Qualtrics	0	-2	1	1
Vs. No Appraisal	0	0	-1	1

To address the potential for type I error inflation due to multiple comparisons, the Benjamini-Hochberg procedure was applied, setting a stringent significance threshold of $p < .005$.

Results

Intention-to-Treat analyses (Gupta, 2011) were conducted to examine whether participants who dropped out of the study were associated with their baseline scores. Our findings indicated that participants who scored higher on the baseline measure of Life Satisfaction (SWLS) were more likely to be retained in the study (*OR* = 1.1, 95% CI [1.01, 1.18]). No other baseline variables moderated retention significantly. Additionally, there were no group differences on key study variables at baseline.

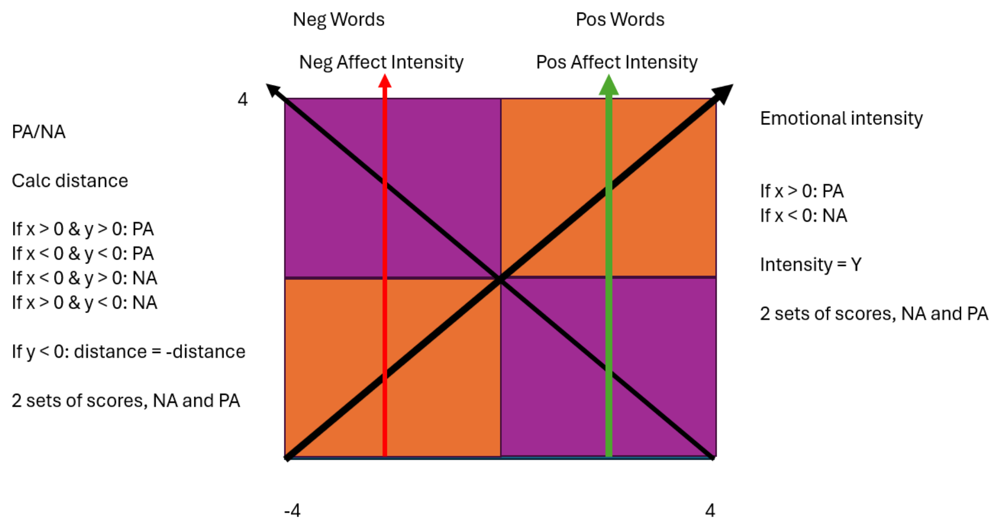
Pre-registered Results

H1. To assess positive and negative affect scores, emotional intensity was calculated based on the distance of the emotion terms from the slope in each quadrant (Russell, 1980; Figure 3). A low correlation was observed between positive and negative mood distance ($r = 0.05$). When only loading positive and negative affect to compose wellbeing at the daily level, the one-factor model explained approximately 5% of the total variance. However, when the appraisal item was added, it resulted in a two-factor model, with positive affect and appraisal loading onto factor 1 and negative affect loading onto factor 2, explaining an increased 34% of the total variance.

Due to concerns about the number of available data points at the daily level for each variable, an exploratory analysis was conducted by clustering users' data into weeks (4 weeks total) and averaging positive affect, negative affect, and appraisal for each week. When only loading average positive affect and average negative affect, the one-factor model explained 8% of the total variance. However, when the appraisal item was included, it again resulted in a two-factor model, with average positive affect and average appraisal loading onto factor 1 and average negative affect loading onto factor 2, explaining an improved 37% of the total variance.

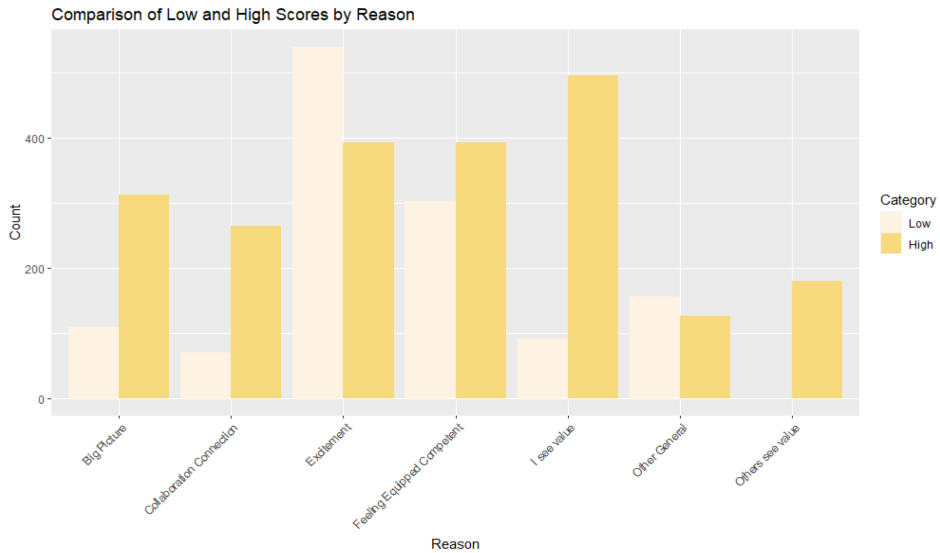
These results suggest that including positive affect, negative affect, and appraisal might be superior relative to only including affective evaluations.

Figure 3. Illustration of Emotional Intensity for Mood Terms Calculation Process



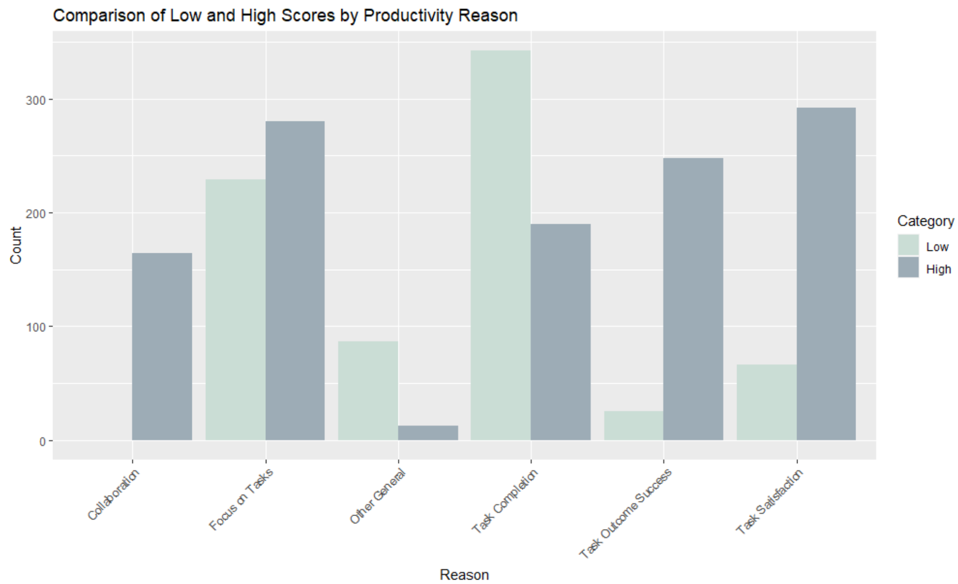
H2. Motivation and productivity ratings were divided into two categories: low (ratings 1 and 2) and high (ratings 3, 4, 5). The frequency count of each motivation reason selected was included (Figure 4). To analyze general patterns among reasons and ratings, positive and negative phrasing reasons were grouped into broader categories. When participants rated low on motivation, they tended to find internal factors to explain the lack of motivation (e.g., “There’s nothing on my to-do list I’m excited about”) instead of using external attributions (e.g., “Others don’t see value in the things I do”). These patterns were statistically significant. The most frequently selected reason for high motivation was “I see value in things I do (i.e., “I see value” category; Figure 4),” while the most frequent reason for low motivation was “There’s nothing on my to-do list I’m excited about (i.e., “Excitement” category; Figure 4).”

Figure 4. Distribution of Motivation Reasons for Low and High Motivation Ratings



The same procedure was applied to productivity, where ratings were grouped into two categories, and negative and positive reasons were grouped into corresponding general categories (Figure 5). Similarly, participants tended to attribute low productivity to internal reasons (e.g., "I didn't complete all the tasks I set out for today") rather than interpersonal reasons (e.g., "I wasn't able to collaborate effectively with others"). These results were statistically significant. The most frequently selected reason for high productivity was "I feel good about what I achieved today (i.e., "Task Satisfaction" category; Figure 5)," and the most chosen low productivity reason was "I didn't complete all the tasks I set out for today (i.e., "Task Completion" category; Figure 5)."

Figure 5. Distribution of Productivity Reasons for Lw and High Productivity Ratings



H3. No individual differences were observed between the choice of motivation or productivity choices.

H4. Both UpBeing groups demonstrated some advantages in improving energy and attitude compared to the Qualtrics condition (Table 4).

Table 4. Comparison of Effects on Attitude and Energy Across Conditions

	State								
	Qualtrics vs. UpBeing1			**Qualtrics vs. UpBeing2**			**UpBeing1 vs. UpBeing2**		
	β	95% CI	p	β	95% CI	p	β	95% CI	p
Attitude	0.14	[-0.08, 0.365]	0.212	0.21	[0.00, 0.42]	0.049	0.07	[-0.17, 0.31]	0.569
Energy	0.27	[0.11, 0.44]	**0.001**	0.18	[0.03, 0.34]	**0.022**	-0.09	[-0.27, 0.09]	0.316
Reference condition	*Qualtrics Condition*			*Qualtrics Condition*			*UpBeing1 Condition*		

Note. Significant p-values were noted in bold.

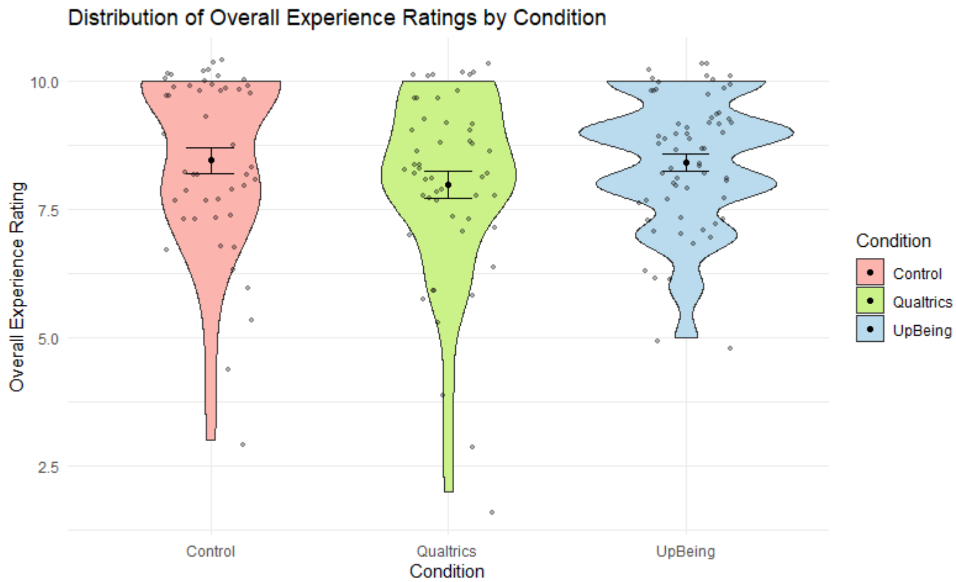
H5. There were no significant differences among groups for overall study ratings (Table 5). However, the lowest rating given in the UpBeing groups (5) was higher than the lowest ratings in both the Control (3) and Qualtrics (2) groups (Figure 6).

Table 5. Overall Experience Ratings Across Conditions

Condition	**N**	**Mean**	**SD**	**Median**	**Min**	**Max**
Control	48	8.46	1.74	8.5	3	10
Qualtrics	51	7.98	1.82	8	2	10

UpBeing	63	8.41	1.29	9	5	10

Figure 6. Overall Experience Ratings Across Conditions



Exploratory Analyses

Study Level (4 weeks; Baseline vs. Post-intervention). No significant differences were observed between UpBeing 1 and UpBeing 2. Therefore, the two groups were combined and compared to the Control and Qualtrics groups.

Table 6. Trait Level Analyses on Target Outcome Variables Across Conditions

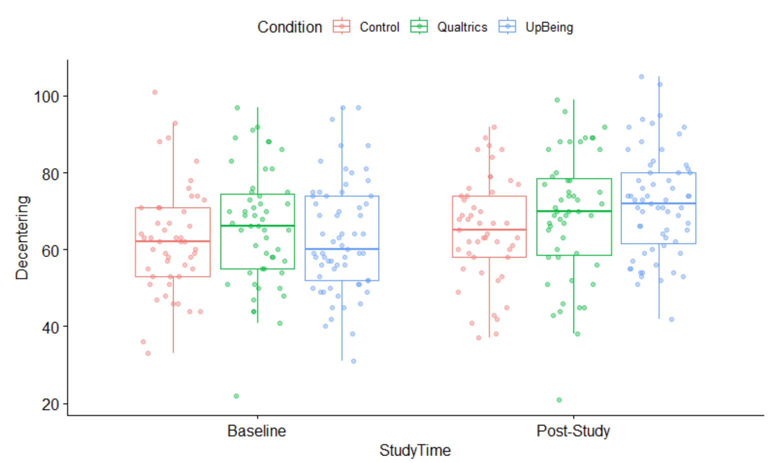
	Trait					
	Control vs. UpBeing			Qualtrics vs. UpBeing		
Decentering	β	95% CI	p	β	95% CI	p
Decentering (total score)	6.06	[1.58, 10.55]	0.008	5.78	[1.20, 10.36]	**0.014**
Awareness	2.21	[0.27, 4.14]	0.025	2.83	[0.64, 5.03]	**0.012**
Nonreactivity	2.73	[0.62, 4.85]	0.012	2.08	[-0.02, 4.18]	0.052
Disidentification	1.12	[-0.98, 3.22]	0.294	0.86	[-1.24, 2.97]	0.420
Reference condition	*Control Condition*			*Qualtrics Condition*		
	Control vs. UpBeing			Qualtrics vs. UpBeing		
Mood	β	95% CI	p	β	95% CI	p
Positive Mood	2.34	[-0.13, 4.82]	0.064	2.07	[-0.35, 4.49]	0.093
Negative Mood	-1.85	[-4.67, 0.96]	0.196	-2.82	[-5.44, -0.20]	**0.035**
Reference condition	*Control Condition*			*Qualtrics Condition*		
	Control vs. UpBeing			Qualtrics vs. UpBeing		

Composed Wellbeing	β	95% CI	p	β	95% CI	p
Positive Factor	0.13	[-0.10-0.37]	0.259	0.22	[-0.00, 0.43]	0.051
Negative Factor	-0.05	[-0.29, 0.19]	0.668	-0.20	[-0.40, -0.00]	**0.045**
Subjective Wellbeing Rating	0.34	[-0.16, 0.83]	0.186	0.47	[0.01, 0.93]	**0.043**
Reference condition	*Control Condition*			*Qualtrics Condition*		

Note. Significant p-values were noted in bold.

Decentering and related Constructs. The UpBeing groups demonstrated advantages in improving the Decentering total score compared to both the Control and Qualtrics groups. Furthermore, UpBeing improved Awareness compared to both the Control and Qualtrics groups and improved Nonreactivity significantly compared to the Control group (Table 6; Figure 7).

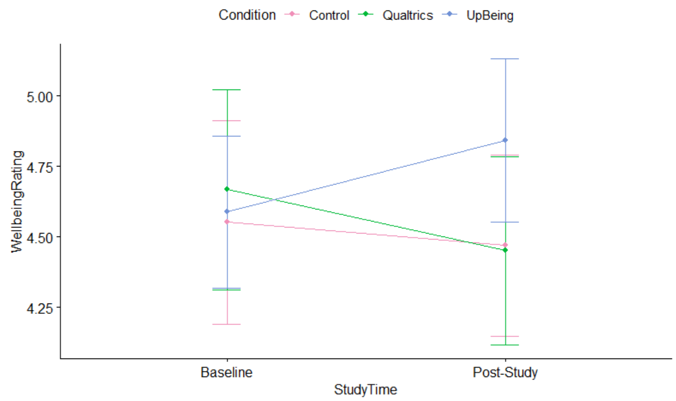
Figure 7. Boxplot Comparison of Decentering Scores Across Conditions at the Study Level



Mood. No significant differences were observed between the Control and UpBeing groups or the Control and Qualtrics groups. However, the UpBeing groups significantly maintained low negative mood relative to the Qualtrics condition (Table 6).

Wellbeing. No significant differences were observed in Composed Wellbeing between the Control and UpBeing groups or the Control and Qualtrics groups. The UpBeing groups again decreased the Negative Factor and improved the overall Subjective Wellbeing rating compared to the Qualtrics group (Table 6; Figure 8).

Figure 8. Subjective Wellbeing Ratings Across Conditions at the Study Level



Relationships between Study Outcomes and Study Experience. Participants' ratings of study experience were generally positively correlated to outcome variables showing weak to moderate positive correlations. Subsequent subgroup analyses suggested that this association was driven by the training groups but was not observed within the control group (Table 7), who did not participate in technology-supported reflection.

Table 7. Significant Correlations Between Target Variable Changes and Overall Study Experience Rating

Condition	Variable	Correlation	P-Value
Intervention Conditions	NegativeMood_change	-0.200	0.031
Intervention Conditions	WellbeingRating_change	0.184	0.048
Intervention Conditions	Reappraisal_change	0.267	0.004
Intervention Conditions	SWLS_change	0.283	0.002
Intervention Conditions	Autonomy_change	0.215	0.021
Intervention Conditions	Competence_change	0.24	0.009
Intervention Conditions	Relatedness_change	0.213	0.022
Intervention Conditions	Productivity_change	0.235	0.011

Note. Only correlations with significant p-values were included.

Sentiment Analysis. Open-ended questions were analyzed using a pretrained model (RoBERTa) in the Python environment. Both the Qualtrics and UpBeing conditions showed greater meeting of expectations compared to the control condition, while only the UpBeing condition showed greater perceived changes compared to the control.

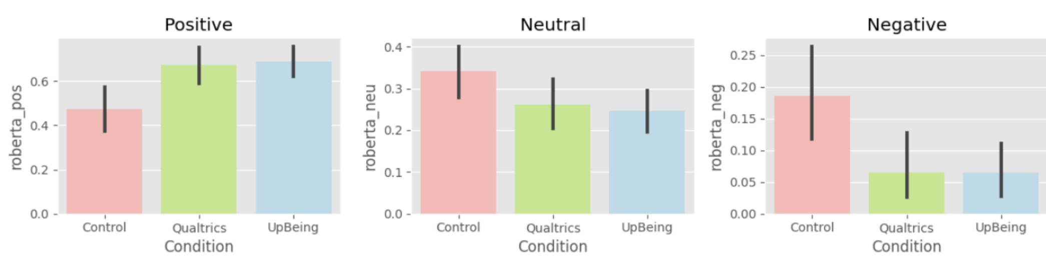
Met Expectations. At the end of the study, participants were asked, "To what degree has the training met your goals and expectations?" After applying the pretrained model, scores for positive, neutral, and negative sentiment were received for each response and condition. Tukey's HSD test results summary showed that the mean values for the positive score for the Qualtrics and UpBeing groups were significantly higher than for the Control group, and the mean values for the negative score were significantly lower than for the Control group (Table 8; Figure 9).

Table 8. Mean Differences and Statistical Analysis of Roberta Positive and Negative Scores on Study Expectations Across Conditions

Roberta Positive Score	**Mean Difference**	**Adjusted P-Value**	**95% CI**
Control vs. Qualtrics	0.20	**0.005**	[0.05, 0.35]
Control vs. UpBeing	0.22	**0.001**	[0.08, 0.36]
Qualtrics vs. UpBeing	0.02	0.96	[-0.12, 0.16]
Roberta Negative Score	**Mean Difference**	**Adjusted P-Value**	**95% CI**
Control vs. Qualtrics	-0.12	**0.01**	[-0.22, -0.02]
Control vs. UpBeing	-0.12	**0.006**	[-0.21, -0.03]
Qualtrics vs. UpBeing	-0.001	1.00	[-0.09, 0.09]

Note. Significant p-values were noted in bold.

Figure 9. Mean Differences and Statistical Analysis of Roberta Positive and Negative Scores on Study Expectations Across Conditions



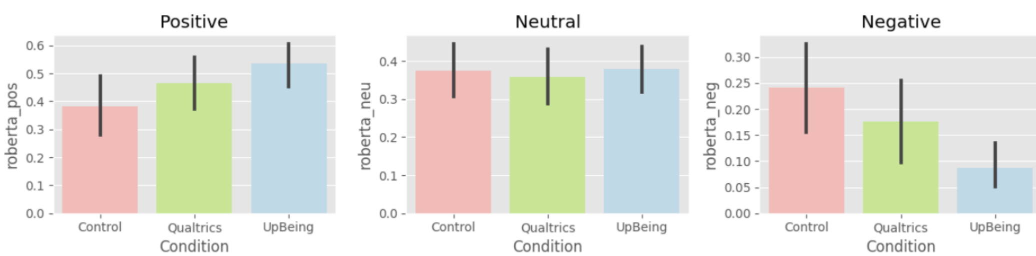
Perceived Change. At the end of the study, participants were also asked, "What did you notice, if anything, that changed about yourself while participating in our study?" The same procedure was conducted, and it was found that the mean values for the negative score for the UpBeing group were significantly lower than for the Control group (Table 9; Figure 10).

Table 9. Mean Differences and Statistical Analysis of Roberta Positive and Negative Scores on Noticed Changes Across Conditions

Roberta Negative Score	Mean Difference	Adjusted P-Value	95% CI
Control vs. Qualtrics	-0.07	0.40	[-0.19, 0.05]
Control vs. UpBeing	-0.15	**0.005**	[-0.27, -0.04]
Qualtrics vs. UpBeing	-0.09	0.16	[-0.20, 0.02]

Note. Significant p-value was noted in bold.

Figure 10. Mean Differences and Statistical Analysis of Roberta Positive and Negative Scores on Noticed Changes Across Conditions



Discussion

The present study examined the benefits of frequent technology-supported wellbeing assessment. Given the heterogeneity of wellbeing check-in measures across both the app marketplace and ecological momentary assessment research space, we also explored the minimal assessment items required for psychometrically-valid wellbeing measurement. Our findings suggest that to capture a more holistic view of wellbeing, in addition to basic positive and negative affect, including an item regarding one's appraisal of life is necessary. This is consistent with the literature on subjective wellbeing (Diener, 1984), which consists of three dimensions: positive affect, negative affect, and life satisfaction. While distinct, these components tend to be correlated, with life satisfaction positively associated with positive affect and negatively with negative affect (Diener et al., 2009).

Regarding platform effectiveness, the UpBeing app significantly enhanced self-reported wellbeing over time compared to similar content delivered via the traditional survey platform Qualtrics. Participants using UpBeing reported higher satisfaction and improved decentering skills compared to both the Qualtrics and control conditions. These findings support our hypothesis that app-based interventions can offer a more dynamic and engaging approach to wellbeing tracking, potentially leading to higher adherence and satisfaction. However, since no other wellbeing apps were assessed in our current study, it is unclear whether the observed benefits are specific to the UpBeing app or if any app-based wellbeing check-in would yield similar results.

The superior user satisfaction scores suggest that the app's improved wellbeing benefits can be attributed to its interactive and user-friendly design, which seems to facilitate a more consistent and reflective engagement with wellbeing activities. This aligns with previous research linking higher engagement in digital health interventions to better health outcomes (Linardon et al., 2019; Peters et al., 2018). UpBeing's personalized feedback likely contributed to its effectiveness, allowing users to receive relevant insights into their mental health status. Our findings also have implications for the Technology Acceptance Model (TAM), suggesting that perceived ease of use and perceived usefulness are critical determinants of users' acceptance and sustained engagement with technology-based health interventions (Charness & Boot, 2016).

From a practical perspective, our study highlights the potential of mobile applications to serve as effective tools for wellbeing monitoring, especially in populations such as university students who are familiar with and receptive to digital solutions (Lattie et al., 2019). Universities and mental health practitioners might consider integrating such technologies into their mental health support structures to enhance accessibility and reduce the stigma associated with seeking help.

What Is the Optimal Dimensionality of Wellbeing?

While the multifaceted nature of wellbeing offers a comprehensive understanding, it also presents challenges in measurement and intervention design. A simplified model of wellbeing is often preferred for practical reasons, particularly in digital health interventions where user engagement is critical (Linardon et al., 2019). Minimalistic approaches, such as focusing on core components like affect and emotions, are easier to implement and more likely to sustain user engagement over time (Bakker et al., 2016; Yardley et al., 2016). These components are interrelated and their combined assessment can effectively gauge an individual's overall wellbeing.

However, a nuanced approach is essential to fully capture the complexity of wellbeing. For instance, the tripartite structure (positive affect, negative affect, and life satisfaction) is widely validated and frequently used in wellbeing research (Busseri & Sadava, 2011; Diener, 1984). These elements provide a more detailed understanding and allow for personalized interventions tailored to individual needs. The inclusion of appraisal items, as evidenced in our study, highlights the importance of capturing reflective evaluations of one's state, beyond just affective assessments. Our findings suggest that while simplicity in measurement (e.g., focusing on affect) is beneficial for maintaining user engagement, incorporating nuanced elements (e.g., life appraisal) is necessary for a more holistic and accurate representation of wellbeing.

Best Practices for User Engagement

User engagement plays a pivotal role in the success of mobile health interventions. High engagement levels are strongly associated with better adherence, increased user satisfaction, and significant improvements in health outcomes (Linardon et al., 2019; Peters et al., 2018). In the present study, user satisfaction ratings were weakly-to-moderately correlated with improvements across a variety of study outcome measures. This finding provides initial empirical support that the users experience is relevant for health and regulatory outcomes. Since this finding is correlational, it is unclear whether engaged users more likely to benefit, or whether greater engagement comes from having noticed positive change from app use. Future research is needed to establish the direction of the engagement outcome relationship.

Based on our study and existing literature, several best practices emerge for fostering deep user engagement in digital wellbeing applications:

Personalization tailored to individual preferences and behaviors is key. Adapting content and interventions to meet users' unique needs and contexts can foster a sense of ownership and relevance, leading to higher completion rates and better outcomes (Yardley et al., 2016). For instance, the personalized feedback provided by the UpBeing app likely contributed to its superior performance in our study.

An aesthetically pleasing and functionally rewarding user experience is essential for maintaining engagement (Sutcliffe, 2010). The design should prioritize ease of use while providing immediate, meaningful feedback that encourages feelings of competence and enjoyment (Beckmann et al., 2022; Hassenzahl et al., 2010).

Leveraging real-time data analysis and ecological momentary assessment (EMA) enables dynamic response to users' changing needs. EMA captures user experiences and behaviors in real-time, offering insights that can tailor interventions more effectively and enhance user engagement (Torous et al., 2021).

To sustain long-term engagement, digital tools must evolve alongside the user’s journey. Periodic updates, fresh content, and adaptive feedback mechanisms can help maintain interest and commitment (Raji et al., 2024). Our study demonstrated that app-based wellness tracking like UpBeing, which offers interactive and personalized experiences, can lead to higher engagement and better wellbeing outcomes compared to traditional survey methods.

By integrating these best practices, digital wellbeing tools can enhance user engagement, thereby maximizing their effectiveness and impact on long-term wellbeing. The insights from our study emphasize the importance of designing user-centric, engaging, and personalized interventions to support mental health and wellbeing.

Limitations and Future Research Directions

One main limitation for the current study was that participants were post-secondary students motivated to complete daily check-ins to receive 3% course credit as compensation. Future research should conduct follow-up analyses to determine whether participants are truly intrinsically motivated to track their wellbeing after the study period ends.

Our study focused solely on subjective wellbeing (positive affect, negative affect, and life satisfaction). We did not include ratings on motivation and productivity in our current wellbeing composition, as not all participants use these check-in items. However, wellbeing encompasses many other important domains (VanderWeele, 2022; VanderWeele et al., 2020) that individuals may wish to track daily (e.g., sleep quality, physical discomfort, financial wellbeing). Future studies could explore including more check-in items to assess the measurement of wellbeing comprehensively and investigate whether user engagement can maintain the same level over time.

Additionally, we relied only on self-reported measures for comparing condition differences. While passive data were provided for participants in UpBeing conditions who consented to connect health apps, this data was not collected for Qualtrics or control groups. Future studies could provide all participants with wearables and retrieve passive data, enabling cross-condition comparisons and a more holistic overview of wellbeing changes.

Some participants expressed hesitancy about downloading a digital app, limiting their participation. The use of digital mental health tools raises concerns around data privacy and security (Gooding, 2019). Detailed discussion on data protection measures, consent management, and ensuring data security is essential. This could cover the ethical implications of data usage and storage, providing reassurance that user data is handled with the utmost care and respect for privacy.

Concluding Remarks

In conclusion, this study provides initial evidence that app-based self-reflection tools like UpBeing can enhance self-reported wellbeing among university students. Exploratory sentiment analysis also suggests that the app-based approach may surpass traditional survey methods in engagement and satisfaction. The findings highlight the potential of digital tools to transform mental health monitoring and intervention, making wellness support more accessible and engaging. By continuing to refine and understand the capabilities of app-based wellness tracking, we can better tailor these tools to diverse global populations' needs, paving the way for a more inclusive and effective approach to mental health care.

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