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# Understanding the role of beliefs on intentions and actual usage of a tool for self-management of mental health among college students

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ABSTRACT

Mental health issues are prevalent among college students, with digital interventions lacking in attempts to reduce participant attrition and address low engagement with technology. This study assessed changes in college students' beliefs regarding mental health after exposure to a digital mental health self-management coaching and education app, the Mental Health Evaluation and Lookout Program (mHELP). Participants' beliefs, measured using constructs from the Health Belief Model and Technology Acceptance Model, were compared to user engagement and changes in scores on validated scales for stress, depression, and anxiety. Participant beliefs including *self-efficacy*, *perceived ease of use*, and *cues to action* became more positive post-intervention. Higher participant *self-efficacy* indicated lower stress, anxiety, and depression ratings. Participants who believed stress to be a serious *health threat* and perceived the app as *useful* and *easy to use* were more likely to engage with the app. Providing digital mental health coaching showed significant relationships between students' beliefs regarding mental health self-management, their engagement with the app, and the reduction in stress and anxiety.

## 1. Introduction

Mental health conditions are prevalent in the US with around 20% of adolescents seeking treatment at some point in their life (Mojtabai and Olfson, 2020). College students are at greater risk, with studies showing up to one third of students have been diagnosed with a mental health issue (Eisenberg et al., 2013). The rate of students who received a mental health diagnosis increased from 22% to 36% between 2007 and 2017 (Lipson et al., 2019), and the COVID-19 pandemic has exacerbated the problem (Son et al., 2020; Wang and Zhao, 2020). There is a timely need to investigate the efficacy of treatments offered to students.

Mental health management approaches include spiritual, psychiatric, and psychosocial treatments (Choudhry et al., 2016). Spiritual treatments, while not clearly defined and well established in the literature, are common and aim to relax patients and put them in a state of comfort. Psychiatric treatments involve diagnosing the condition and prescribing medication to the patient, while psychosocial treatment includes structured counseling, psychotherapy, and case management to help mitigate stress and anxiety (Choudhry et al., 2016; National Alliance on Mental Illness, n.d.). Such in-person consultations, however, face several limitations including the requirement to visit and spend time with the counselor/therapist, as well as the high costs associated with regular scheduling. In addition, evidence suggests college students underutilize mental health resources and services (Son et al., 2020).

Digital mental health interventions have become an increasingly popular approach to offer affordable and flexible mental health services to patients requiring mid to low intensity mental health support (Price et al., 2012). These interventions can be provided through a variety of means; the most popular platform of which may be via smartphone applications (apps) and thus categorized as mobile health (mHealth) interventions. Such digital interventions have generally been found effective in improving the mental health of participants (Karyotaki et al., 2017) yet face many challenges. Most importantly, low adherence and engagement rates remain problematic, which jeopardizes the efficacy of long-term treatment plans (Baumel et al., 2019; Linardon and Fuller-Tyszkiewicz, 2020), especially among college students (Lee and Jung, 2018). In fact, there is limited attention in the literature to the elements of cognitive ergonomics such as motivation and the factors influencing user engagement with a digital health tool aimed at improving mental health. As such, there is a general gap and a critical need to investigate approaches to minimize participants' attrition and improve user engagement with mental health interventions (Linardon

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and Fuller-Tyszkiewicz, 2020).

To address this gap, there have been recent calls for incorporating theories from human factors, cognitive ergonomics, and behavioral sciences in developing mental health interventions (DeLucia, 2011; Heiden et al., 2017). Constructs related to health beliefs and perceptions have been used to investigate the levels of engagement with health-related technologies (Dou et al., 2017), as well as changes in clinical outcomes (Pinar and Pinar, 2020). In our previous work, we assessed the efficacy of using behavioral constructs from the Health Belief Model (HBM) and Technology Acceptance Model (TAM) to understand intentions or actual usage of mHealth interventions (Zahed et al., 2023). While our findings suggest that health beliefs may be used as early indicators of intentions to engage with mHealth interventions, the focus was on chronic diseases such as hypertension and it is not clear if the findings generalize to mental health interventions and their sustained usage. Previous research has shown a relationship between several beliefs such as the religious beliefs (Koenig, 2012), the importance of social support from loved ones (Kolstad and Gjesvik, 2014), and barriers to treatment such as social stigma (Shannon et al., 2015); however, little focus has been given to understanding if health beliefs or acceptance of interventions are related to intention and motivation to engage or use such interventions.

Addressing this gap will help proactively assess whether participants will sustain engagement with an intervention, with resultant changes in health outcomes. Therefore, this study aimed to assess changes in participants' beliefs regarding a mHealth intervention program, designed to engage college students in self-managing their mental health. Participants' belief constructs were compared to their intentions, engagement with the platform, and mental health outcomes.

### 1.1. Background and hypotheses

To quantify participants' beliefs, several constructs were integrated from the HBM (Janz and Becker, 1984) and TAM (Davis, 1989). HBM, which has been commonly utilized to relate individuals' health beliefs to their behavioral intention, may benefit from additional constructs adapted from TAM in use cases related to technology engagement (Dou et al., 2017, p. 20). The *resistance to change* (RTC) construct was also added to the model as it has been found to significantly influence intention and behavior in other studies (Dou et al., 2017; Zahed et al., 2023).

Accordingly, several hypotheses were formed based on prior studies on these constructs (Janz and Becker, 1984; Venkatesh, 2000), other mental health interventions (Borghouts et al., 2021), and self-management and education app studies in other health behavior domains (Zahed et al., 2022; Zahed et al., 2023).

*Perceived health threat* (PHT) quantifies how strongly an individual perceives that their condition poses a threat to their health (Janz and Becker, 1984). *PHT* has been found to influence both intention and adherence behavior for mHealth self-management applications (Zahed et al., 2023). It was hypothesized that a higher *PHT regarding mental health will positively affect intention to use the intervention* (H1a), and *engagement with the app* (H1b). One approach to influence PHT is to provide education addressing the risks of certain behaviors. For example, in one study, educating nurses on the risks of drowsy driving caused a significant increase in their *perceived health threat* (Zahed et al., 2022). Therefore, we hypothesize that *educational material provided in the intervention will positively influence participants' PHT regarding mental health* (H1c).

*Self-efficacy* (SE) relates to an individual's confidence in adapting to a new behavior; a construct which was added to the HBM later (Rosenstock et al., 1988). SE has been found to positively influence behavioral intention to use interventions (Janz and Becker, 1984); therefore, we hypothesize that *stronger SE will positively influence intention to use the app* (H2a). Higher SE has also been posited to influence engagement with mental health interventions (Borghouts et al., 2021); therefore, we hypothesize that *higher SE positively influences more engagement with the app* (H2b). We also hypothesize that as participants find benefit in the intervention and witness successful improvement in their outcomes, the *mental health outcomes will positively correlate with SE scores* (H2c). Additionally, *SE* has shown to significantly increase throughout a coaching intervention for hypertension self-management (Zahed et al., 2023). Therefore, we hypothesize that *the intervention group will witness a significant increase in their SE* (H2d).

*Cues to action* (CTA) reflects how strongly an individual recalls performing the required tasks or behaviors. CTA has shown to influence a higher intention to perform health behaviors (Janz and Becker, 1984). Therefore, we hypothesize that *cues to action will positively influence intention to manage one's mental health* (H3a). A previous study showed significant improvements in CTA using a coaching intervention which utilized reminders to perform blood pressure measurements (Zahed et al., 2023). Since the intervention in this study involves similar digital coaching and reminders to use mental health self-management interventions (e.g., breathing exercises), we hypothesize that *higher CTA would positively influence participants' engagement with the app* (H3b), and that *CTA will increase significantly after exposure to the intervention* (H3c).

*Perceived barriers* refers to obstacles to an individual performing a health-related behavior (Janz and Becker, 1984). Such barriers will likely lower participants intentions to engage with interventions (Kontos et al., 2014). We hypothesize that *higher perceived barriers will negatively influence individuals' intention to engage with the app* (H4a). In addition, exposure to barriers after using the interventions may influence the perception of such barriers. Therefore, we hypothesize that *participants with low engagement will have higher perceived barriers* (H4b).

Next, constructs from TAM were evaluated. *Attitude* (ATT), refers to the individual's feelings towards performing the behavior or utilizing an intervention (Davis, 1989), and has been found to positively influence intention to use technology (Venkatesh, 2000). Therefore, we hypothesize that the initial *attitude towards mental health self-management using an mHealth app will positively influence the intention to utilize the app* (H5a), and *actual engagement* (H5b). We also believe that since we utilize content from credible mental health sources, then that should positively influence our participants' attitude (Direito et al., 2018). Accordingly, we hypothesize that *the intervention group should witness a significant improvement in their attitude towards the self-management of mental health* (H5c).

*Perceived usefulness* (PU) is a core construct of TAM and reflects how beneficial a technology is perceived by the individual to help achieve a certain goal. *PU* is believed to positively influence the use of technology (Davis, 1989), and therefore we hypothesize that *perceived usefulness* will *positively impact intention to utilize the mental health self-management intervention* (H6a) and *engagement with the app* (H6b). Given the team's effort to utilize user-centered design approaches to design the interventions, we hypothesize that *perceived usefulness will increase after exposure to the intervention* (H6c). In addition, *perceived usefulness* has been associated with improved health outcomes in a previous study evaluating self-management of hypertension (Zahed et al., 2023). Therefore, we hypothesize that *higher perceived usefulness of the intervention will influence participants' mental health outcomes* (H6d).

*Perceived ease of use* (PEOU) is generally related to how easy to use a technology is as perceived by the individual (Davis, 1989). *Perceived ease of use* has been shown to positively influence *perceived usefulness* and in turn leads to better engagement with technologies (Rho et al., 2014). Therefore, we hypothesize that *stronger perceived will positively influence user engagement with the app* (H7a). We also hypothesize that, as participants get familiar with the app, their *perceived ease of use will increase over time* (H7b).

Previous research has extended TAM to include *social influence (SI)* (Malhotra and Galletta, 1999). *SI* considers the influence of the individual's social circle as well as their level of support on behavior. A strong *SI* and less stigma has been linked with being more open to seeking mental health treatment (Griffiths and Christensen, 2010);

therefore, we hypothesize that a *strong social influence will positively influence intention to use the app* (H8a) and actual *engagement with the app* (H8b).

Finally, *resistance to change (RTC)*, from the Dual Factor Model (Cenfetelli, 2004), assesses if inhibiting beliefs exist regarding performing the behavior. RTC has been found to negatively influence intention (Dou et al., 2017; Nov and Ye, 2008). Therefore, we hypothesize that *resistance to change will negatively influence intention to use the app* (H9a) and *user engagement with the app* (H9b).

## 2. Methods

### 2.1. Study design

The study was part of a larger research effort aimed at evaluating the efficacy of mHealth coaching combined with stress detection technology for improving the mental health of college students over a 10-week period which was deemed appropriate to accommodate students' academic schedule and aligned well with Singh et al.'s (2024) suggestion that 59–66 days is enough for a habit to form. The findings related to stress detection and impact of the intervention on clinical outcomes related to mental health will be reported elsewhere. Participants were sequentially randomized into either intervention or control group using a 3:1 allocation to increase the possibility of detecting changes within the intervention group yet still maintaining a sufficiently sized control group. An a-priori power analysis was conducted using G*power v3.1 to determine the sample size for the study hypotheses (Faul et al., 2007). To achieve 80% power, a medium effect size, and a significance criterion of $\alpha = .05$ the required sample was (N = 56). A larger number of participants was recruited to account for attrition, which has been reported to be up to 50% of individuals diagnosed with mental health issues (Seidler et al., 2021). The study utilized a custom-designed app called Mental Health Evaluation and Lookout Program (mHELP) to provide digital coaching and support self-management of mental using various activities such as breathing and focus exercises, motivational quotes, journaling, among others listed in Appendix Table A.1. The control group did not have any access to the mHELP app, and both groups were asked to complete weekly mental health self-assessments as well as maintain confidentiality of the study details. Furthermore, the intervention group received digital coaching in the second 5-week period of the study only.

### 2.2. Participants

A bulk mail was sent to a large university community in the southern United States to recruit participants. Only adult (≥18 years of age), English-speaking participants owning an iPhone with at least iOS14 were included. Additionally, participants were included only if they received support from the local university counseling services and had to score above a 7 on the Generalized Anxiety Disorder (GAD-7) scale (which indicates a probable disorder and at least moderate anxiety symptoms). Participants with severe anxiety/panic attacks, a history of suicidal attempt, current suicidal ideation, or current self-harm were excluded.

### Ethics approval

The study was approved by the Texas A&M University Institutional Review Board and all participants signed a consent form prior to commencing the study.

### 2.3. Study procedures

Participant beliefs were elicited via a questionnaire given at the beginning, middle (when digital coaching features were unlocked), and end of the study. Ten constructs were measured with at least 2 questions each using Likert scales from 1 to 7 (1 = strongly disagree and 7 = strongly agree). Mental health outcomes were measured using perceived stress scale (PSS-10; Cohen, 1988), patient health questionnaire (PHQ-8; with the question on suicidal thoughts dropped from the original PHQ-9) for depression (Kroenke et al., 2001), and GAD-7 for anxiety (Spitzer et al., 2006) on a weekly basis. Engagement metrics were also assessed as the total number of features utilized. If participants utilized a feature for more than a predetermined target, then they earned a gold medal for engagement (see Appendix Table A.1 for achievement criteria).

### 2.4. Analysis

Cronbach's alpha was used to test for reliability among constructs with more than 2 questions. Constructs with only 2 questions were assessed for reliability via Spearman's correlation. A Kruskal-Wallis test for non-parametric data was used to detect significant change in the behavioral constructs through the course of the intervention (Kruskal and Wallis, 1952). A p-value of 0.05 was used as a cutoff for significance. Engagement levels were divided into two groups: active and non-active participants. Participants who received at least 2 gold medals in the study (See Appendix Table A.1), were considered active participants, while others would be marked as not active. A Kruskal-Wallis test was also used to check for significant differences in beliefs for the two engagement groups (active vs. non-active). The magnitude and significance of causal relationships between the dependent variable (DV) and the independent variables was assessed using a Partial Least Square (PLS) regression analysis to find which belief constructs are significant predictors of *intention* and mental health scores. All analyses were performed on *RStudio version 1.1.447* (Rstudio Team, 2016).

## 3. Results

### 3.1. Demographic information

A total of 129 participants enrolled in the study. Of the total number, 32 participants were assigned to the control group and the remaining 97 to the intervention group. Mean age for all participants was 22.24 years (SD = 4.27, Range = 18–37). Females constituted the majority of participants (70.73%), and half of participants identified as white (50%). 36.58% of participants were graduate students and the remaining were undergraduate students. See Table 1 for a breakdown of demographics for the two groups. Of the initial 97 participants in the intervention group, 82 completed both the pre-post beliefs questionnaires.

**Table 1**
Participant demographics.

| | Intervention (N = 82) | | Control (N = 32) | |
|---|---|---|---|---|
| Age (mean years, standard deviation) | 22.24 | 4.27 | 22.97 | 4.97 |
| Gender (n, %) | | | | |
| Female | 58 | 70.73 | 30 | 93.75 |
| Male | 22 | 26.83 | 2 | 6.25 |
| Non-binary | 1 | 1.22 | 0 | 0 |
| Prefer not to say | 1 | 1.22 | 0 | 0 |
| Race (n, %) | | | | |
| Asian | 25 | 30.48 | 10 | 31.25 |
| Black or African American | 4 | 4.87 | 0 | 0 |
| Native American or Alaskan Native | 2 | 2.44 | 0 | 0 |
| Other | 2 | 2.44 | 1 | 3.125 |
| Prefer not to say | 4 | 4.87 | 1 | 3.125 |
| White or Caucasian | 41 | 50 | 20 | 62.5 |
| 2 or more | 4 | 4.87 | 0 | 0 |
| Class standing (n, %) | | | | |
| Freshman | 8 | 9.75 | 4 | 12.5 |
| Sophomore | 14 | 17.07 | 2 | 6.25 |
| Junior | 22 | 26.83 | 5 | 15.625 |
| Senior | 8 | 9.75 | 10 | 31.25 |
| Graduate Student | 30 | 36.58 | 11 | 34.375 |

Participants who did not complete either the pre or post questionnaires were excluded from the beliefs analysis below.

### 3.2. Reliability measures

Most constructs had a strong reliability measure marked by Cronbach's alpha of *intention* had a Cronbach's alpha of (α = .69), *perceived health threat* (α = .73), *self-efficacy* (α = .78), *social influence* (α = .77), *perceived barriers* (α = .72), *past experience* (α = .81), *resistance to change* (α = .82), *perceived ease of use* (α = .86), and *CTA* (α = .69), all showed adequate reliability. *Attitude* and *perceived usefulness* had 2 questions and a Spearman's correlation of 0.65 ($P < .001$), and 0.48 ($P < .001$) respectively. Table 2 shows questions asked for each construct as well as the construct's reliability score.

**Table 2**
Belief constructs and corresponding questions.

| Construct | Questions | Reliability Measure |
|---|---|---|
| Attitude | This intervention will motivate me to regularly manage my stress.<br>I don't believe that I will be motivated to manage my stress through this intervention | 0.65 |
| Perceived Usefulness | I think the app activities will help me manage my stress.<br>I don't feel this intervention is worth my time and energy. | 0.48 |
| Intention | I would really like to manage my stress better.<br>I don't really want to manage my stress.<br>I would like to perform the app tasks regularly.<br>I don't want to regularly perform breathing exercises. | 0.69 |
| Perceived Health Threat | I am not concerned about the risk of stress on my health.<br>I am not concerned about the risk of stress on my life.<br>If I don't manage my stress, my health may deteriorate.<br>I feel stress is dangerous to my health. | 0.73 |
| Self-Efficacy | I am confident that I know how to manage my stress.<br>I don't feel confident enough to manage my stress.<br>I can manage my stress whenever I feel it coming.<br>I am confident that stress is not a major issue in my life. | 0.78 |
| Social Influence | People who are important in my life encourage me to manage my stress better.<br>I do not feel encouraged by the people around me to manage my stress better.<br>My close circle is supportive towards my mental health. | 0.77 |
| Barriers | There are barriers to managing my stress.<br>I do not feel there are barriers to manage my stress.<br>I am unable to manage my stress.<br>It is easy to manage my stress. | 0.72 |
| Resistance to Change | I do not want this app to change the way I deal with stress.<br>I would like this app to change how I deal with stress.<br>I am open to learning more on how I can manage my stress.<br>It is important to know what I can change to improve my mental health. | 0.82 |
| Perceived Ease of Use | I am able to use this app without much time and energy.<br>Using the app was very easy for me.<br>I do not think the app is easy to use. | 0.86 |
| Cues to Action | I always remember to do take some time and relax.<br>I tend to forget to take some time and manage my stress.<br>I regularly perform activities that manage my stress. | 0.69 |

### 3.3. Belief changes

#### 3.3.1. Control

In the control group, only two constructs changed significantly. *Intention* showed a significant decrease ($H$ (1) = 10.36, $P$ = .001) from ($Mdn$ = 5.75) to ($Mdn$ = 5) and *social influence* significantly increased ($H$ (1) = 5.2, $P$ = .022) from ($Mdn$ = 4.67) to ($Mdn$ = 5.67). Table 3 shows the changes in beliefs between the start and completion of the study.

#### 3.3.2. Intervention

Participants who were exposed to the intervention had significant improvements in their *self-efficacy*, *cues* to *action*, and *perceived ease of use*. *Self-efficacy* improved through the course of the intervention ($H$ (1) = 23.45, $P$ < .001) from ($Mdn$ = 3.25) to ($Mdn$ = 4.25) which supports H2d. *Cues to action* significantly changed ($H$ (1) = 7.96, $P$ = .007) from ($Mdn$ = 3.33) to ($Mdn$ = 3.67) thereby supporting H3c. Perceived ease of use improved ($H$ (1) = 8.32, $P$ = .004) from ($Mdn$ = 5.33) to ($Mdn$ = 5.83), thus supporting H7b. No other constructs changed significantly. Belief means and significant changes are summarized in Table 4.

### 3.4. Beliefs and intention

*Intention* was significantly predicted ($R^2$ = .53, $F$ (10,71) = 7.40, $P$ < .001) by three constructs (Fig. 1). Stronger *perceived health threat* and higher *perceived usefulness* were associated with a positive increase in *intention* (β = .35, $P$ < .001 and β = .25, $P$ = .033, respectively) thereby supporting H1a and H6a. Participants who were more *resistant to change* were less likely to intend to use the intervention (β = -.29, $P$ = .027), supporting H9a. No other hypotheses referring to constructs predicting intention (i.e., H2a, H3a, H4a, H5a, H8a) were supported.

### 3.5. Beliefs and engagement

On average, the active group had around 4.45 gold medals earned for actively engaging with the app, while the non-active group had around 0.3 gold medals. Participants from the active group had a significantly higher ($H$ (1) = 4.59, $P$ = .032) *perceived health threat* ($Mdn$ = 5.875) compared to the non-active group ($Mdn$ = 6.5) which supports H1b. *PU* was also significantly higher ($H$ (1) = 4.49, $P$ = .034) among participants from the active group ($Mdn$ = 5.5) compared to the non-active group ($Mdn$ = 5.25), supporting H6b. *Perceived Ease of Use* was significantly different ($H$ (1) = 11.73, $P$ < .001) between the two engagement groups with the active group rating the app higher ($Mdn$ = 6.33) compared to non-active group ($Mdn$ = 5.33), supporting H7a. *INT* was also significantly higher ($H$ (1) = 3.95, $P$ = .047) among participants from the active group ($Mdn$ = 5.875) compared to the non-active group ($Mdn$ = 5.25). Other constructs did not differ across engagement groups. Table 5

**Table 3**
Changes in belief means for the control group.

| Construct | Pre | Post | KW[a] |
|---|---|---|---|
| INT | 5.65 | 4.8 | $P$ = .001[b] |
| PEOU | 5.35 | 5.64 | $P$ = .47 |
| SE | 3.23 | 3.56 | $P$ = .22 |
| PU | 4.94 | 4.55 | $P$ = .35 |
| RTC | 2.26 | 2.29 | $P$ = .33 |
| CTA | 2.96 | 2.91 | $P$ = .83 |
| PHT | 6.02 | 5.85 | $P$ = .36 |
| ATT | 4.65 | 4.48 | $P$ = .91 |
| SI | 4.89 | 5.59 | $P$ = .022[b] |

[a] KW: Kruskal-Wallis test.
[b] Denotes significance.

**Table 4**
Changes in belief means over the course of the study and respective significance.

| Construct | Pre | Mid | Post | KW[a] Pre-Mid | KW[a] Mid-Post | KW[a] Pre-Post |
|---|---|---|---|---|---|---|
| INT | 5.7 | 5.48 | 5.5 | $P = .31$ | $P = .84$ | $P = .138$ |
| PEOU[b] | 5.06 | 4.62 | 5.52 | $P = .06$ | $P < .001$[b] | $P = .004$[b] |
| SE[b] | 3.14 | 3.31 | 3.95 | $P = .37$ | $P < .001$[b] | $P < .001$[b] |
| PU | 5.28 | 4.77 | 5.19 | $P < .001$[b] | $P < .05$[b] | $P = .97$ |
| RTC | 1.95 | 2.16 | 2.11 | $P = .13$ | $P = .76$ | $P = .17$ |
| CTA[b] | 3.30 | 3.52 | 3.83 | $P = .224$ | $P = .06$ | $P = .007$[b] |
| PHT | 5.98 | 5.84 | 5.88 | $P = .91$ | $P = .70$ | $P = .66$ |
| ATT | 5.29 | 4.83 | 5.16 | $P < .05$[b] | $P = .18$ | $P = .43$ |
| SI | 5.52 | 5.53 | 5.78 | $P = .68$ | $P = .13$ | $P = .09$ |
| BAR | 4.97 | 4.88 | 4.65 | $P = .65$ | $P = .11$ | $P = .06$ |

[a] KW: Kruskal-Wallis test.
[b] Denotes significance.

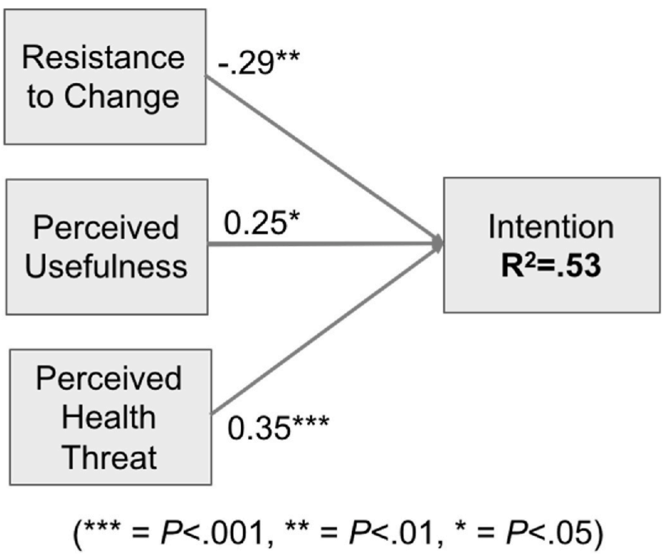


**Fig. 1.** Relationship between constructs and intention.

**Table 5**
Belief means across engagement levels.

| Construct | Not Active | Active | KW[a] |
|---|---|---|---|
| INT[b] | 5.29 | 5.66 | $P = .047$[b] |
| PEOU[b] | 5.13 | 5.89 | $P < .001$[b] |
| SE | 3.93 | 3.97 | $P = .89$ |
| PU[b] | 4.9 | 5.46 | $P = .034$[b] |
| RTC | 2.21 | 2.02 | $P = .17$ |
| CTA | 3.80 | 3.84 | $P = .96$ |
| PHT[b] | 5.64 | 6.1 | $P = .032$[b] |
| ATT | 5.06 | 5.25 | $P = .34$ |
| SI | 5.63 | 5.92 | $P = .16$ |
| BAR | 4.71 | 4.59 | $P = .40$ |

[a] KW: Kruskal-Wallis test.
[b] Denotes significance.

summarizes the mean scores for each construct and significance level of a detected change.

### *3.6. Beliefs and clinical outcomes*

Mean mental health scores at the beginning of the coaching were analyzed using a PLS regression to relate these outcome scores to participant beliefs. The results showed that participants with higher *self-efficacy* had a lower score for all 3 different mental health scores assessed. Specifically, higher *self-efficacy* was associated with a lower score on PHQ-8 ($\beta = -2.06$, $P = .002$), a lower score on GAD-7 ($\beta = -2.21$, $P = .002$), and a lower score on PSS-10 ($\beta = -1.98$, $P = .041$), supporting H2c. More *perceived barriers* contributed to a higher score only for PHQ-8 ($\beta = 1.71$, $P = .025$). Table 6 summarizes the support or lack thereof for each hypothesis. The full account of mental health outcomes is outside the scope of this paper and will be reported elsewhere.

## 4. Discussion

The study evaluated the efficacy of using various beliefs constructs from HBM and TAM to show relationships with intentions and engagement with a mobile health application to self-manage and improve outcomes among a sample of college students. While both intervention

**Table 6**
Hypotheses status and significance.

| Hypotheses | Status | Significance |
|---|---|---|
| (H1a) Higher PHT regarding mental health will positively affect intention to use the app | Supported | $\beta = 0.35$ $P < .001$ |
| (H1b) Higher PHT regarding mental health will positively affect engagement with the app | Supported | $P = .032$ |
| (H1c) Intervention will positively influence participants' PHT regarding mental health | Not Supported | – |
| (H2a) Stronger SE will positively influence intention | Not supported | – |
| (H2b) Higher SE positively influences more engagement with the app | Not supported | – |
| (H2c) Successful improvement in their outcomes should reflect with a higher SE score | Supported | $P < .05$ |
| (H2d) Intervention group will witness a significant increase in their SE | Supported | $P < .001$ |
| (H3a) CTA will positively influence intention to manage one's mental health | Not Supported | – |
| (H3b) Higher CTA would positively influence participants' engagement with the app | Not Supported | – |
| (H3c) CTA will increase significantly after exposure to the intervention | Supported | $P = .007$ |
| (H4a) Higher perceived barriers will negatively influence individuals' intention to engage with the app | Not Supported | - |
| (H4b) Participants with low engagement will have higher perceived barriers | Not Supported | – |
| (H5a) Attitude towards mental health self-management using an mHealth app will positively influence the intention to utilize the app | Not Supported | – |
| (H5b) Attitude towards mental health self-management using an mHealth app will positively influence engagement with the app | Not Supported | – |
| (H5c) The intervention group should witness a significant improvement in their attitude towards the self-management of mental health | Not Supported | – |
| (H6a) Perceived usefulness will positively impact intention to utilize the mental health self-management intervention | Supported | $\beta = 0.25$ $P = .033$ |
| (H6b) Perceived usefulness will positively impact actual engagement with the app | Supported | $P = .034$ |
| (H6c) Perceived usefulness will increase after exposure to the intervention | Not supported | – |
| (H6d) Higher perceived usefulness of the intervention will influence participants' mental health outcomes | Not supported | – |
| (H7a) Stronger perceived will positively influence user engagement with the app | Supported | $P < .001$ |
| (H7b) As participants get familiar with the app, their perceived ease of use will increase over time | Supported | $P = .004$ |
| (H8a) Strong social influence around a person to manage their mental health would case an increase in intention to use our app | Not Supported | – |
| (H8b) Strong social influence will positively influence actual engagement with the app | Not Supported | – |
| (H9a) Resistance to change will negatively influence intention to use the app | Supported | $\beta = -0.29$ $P = .027$ |
| (H9b) Resistance to change will negatively influence user engagement with the app | Not Supported | – |

and control groups had similar belief scores at the beginning of the study, the findings suggest that the intervention has led to positive changes in several participant beliefs contributing to a general gap in understanding changes in belief constructs over time. Additionally, significant differences in beliefs were found between the two engagement groups (active vs. non-active). Next, we discuss some of the interesting findings from our study.

*Intention* did not change over the course of the study for the intervention group, perhaps because participants initially rated their *intentions* to use the intervention highly and thus the intervention features users received matched their expectations. Another possibility that may have hindered a positive increase in *intention* could be the disturbance from the stress detection alerts as reported in some of the post-study interviews. On the other hand, *intention* decreased for the control group who did not receive the intervention. In addition, stronger *perceived health threat* and higher *perceived usefulness* predicted *intention* and those with high engagement with the intervention had high *PHT* and *PU*. This finding may suggest that these two constructs may be used proactively to assess future engagement with mHealth apps, but this notion needs further examination.

In line with previous studies (e.g., Zahed et al., 2022), *perceived health threat* was the most important predictor of *intention*. It seems that those who take their condition seriously are more motivated to engage in self-care. When using digital technology, it appears that high PHT may influence motivation and intention to engage with technology and achieve set goals as explained by the application of motivation theory to human-technology interaction (Szalma, 2014). However, those who do not perceive a major health threat may not adopt or engage in mental health self-management. Such low *PHT* may be due to low health literacy which has been found to be a major obstacle to seeking treatment (Gulliver et al., 2010). Indeed, previous research showed that low perceived need among mild to moderate mental health cases is a primary reason for not seeking mental health treatment (Griffiths and Christensen, 2010)). While we anticipated that our intervention and the education material provided would raise awareness and increase the *PHT*, perhaps due to the nature of educational content which were more biased towards self-management. Future work may evaluate digital coaching that includes information about the risks and negative outcomes related to mental health issues to evaluate changes to *PHT*.

*Perceived usefulness* was another major predictor of *intention* to use the app and was significantly higher for the active group. Analysis of changes to *PU* showed that this construct did not change significantly, perhaps due to high initial perceptions. Generally, attaining high levels of both *PEOU* and *PU* can be achieved by evaluating the interface and incorporating user needs (Szalma, 2009), and performing usability studies on the app to guarantee its ease of use and usefulness (Lewis, 2014). More work is needed to validate the impact of *PU* as well as *PHT* and *resistance to change* on intentions and utilize them for behavior change.

One construct that improved significantly during the intervention period was *self-efficacy*. We believe this is due to the intervention serving its purpose of empowering participants to feel more confident in their self-management regimen. However, while previous work has shown participants' *self-efficacy* to be a facilitator of user engagement with digital mental health interventions (Borghouts et al., 2021), in our study, we did not observe such relationship. In other words, both active and non-active groups had similar *self-efficacy*. This might be due to participants employing other self-management regimens independent of the study intervention. However, higher SE scores reflected better mental health scores on all three mental health metrics. This finding is in line with previous evidence suggesting that stronger perceived *self-efficacy* may minimize the effects of stress (Schönfeld et al., 2016) and improve the outcomes of digital mental health interventions (Clarke et al., 2014). Given the importance of this construct, *self-efficacy* should be strengthened by understanding user needs and designing interventions using HFE guidelines to ensure participants are sufficiently motivated to adhere to a self-management regimen, set achievable goals, and provide any resources and education needed to achieve these goals (Direito et al., 2018; Szalma, 2009).

*Cues to action* also improved over the course of the intervention. This may be due to regular reminders to utilize the app which has been shown to be effective in habit formation (Liu and Willoughby, 2018). A similar positive trend in CTA was observed in a previous study on hypertension self-management using a mHealth platform (Zahed et al., 2023). This previous study also documented a significant relationship between internal *cues to action* and adherence to blood pressure measurements. However, in this study, those who had stronger *cues to action* did not engage more with the app.

*Perceived barriers* decreased slightly after the intervention phase and was slightly lower for the active group who utilized the app more. More importantly, those who had stronger *perceived barriers* had worse depression outcomes. Interventions aiming at lowering *perceived barriers* may find benefit in understanding participants' *barriers* to engaging with the treatment intervention such as participants' negative experiences with the treatment provider or the treatments' low efficacy (Griffiths and Christensen, 2010; Wieling et al., 2015).

### *4.1. Limitations and future work*

Several limitations may impact this study's generalizability. First, the sample population was all recruited from one university campus, so the findings may not generalize to all students. Similarly, the study was limited to iPhone users with relatively new operating systems (iOS 14) and the results may not generalize to other platforms, older iPhones, or those who do not own smartphones. Second, various events during students' academic schedule such as exams may have influenced their engagement metrics and mental health. More work is warranted to account for such variations in future investigations. In addition, the student population may be more aware of mental health issues and may be open to learning more about them, which may suggest selection bias. However, the participants are also young which could indicate that they are not well adapted to managing stressors in life and mental health. Future research is warranted to assess more diverse and older populations as opposed to our student population.

Fourth, this study relied heavily on self-reported data, which is prone to several biases, including social desirability and recall biases. Future work can compare these findings with objective measures such as clinical assessment or behavioral tracking or triangulate data through combining self-reported data with other observations such as clinical records. Belief questionnaires may also be elicited more frequently study to better assess trends but may risk fatiguing participants. Further work may also be warranted to validate the belief constructs used in our integrated model.

Fifth, the engagement scoring system we used has not been validated. Unfortunately, there seems to be a general gap in reliable and validated engagement scoring mechanisms that warrants more work. Future work can improve and validate the engagement metric proposed in this research and additional metrics such as average time app has been used, frequency of using the app, most visited pages may be added to provide a more holistic understanding of user engagement. Finally, as this was a naturalistic study, we did not have control over potential confounding variables that could have influenced changes in beliefs, behaviors, or mental health scores for our participants. For example, while the control group did not have access to the app, they may have discussed the study with their peers who may have been in the intervention group even though we encouraged participants to maintain confidentiality about their participation in the study.

### *4.2. Conclusion*

The digital mental health intervention provided through a mobile platform showed promise in positively improving students' beliefs regarding self-management of their mental health. Health beliefs showed predictive efficacy for engagement with digital mental health interventions, which highlights the useful impact of utilizing the assessment of participant beliefs when researching user engagement and adherence. Given the potential importance of *perceived health threat* and *self-efficacy* to the success of digital interventions, we recommend that programs should focus on equipping participants with the tools they need to feel confident in their regimen and highlighting the health and performance risks of mental health issues to ensure a more positive engagement with similar interventions.

## CRediT authorship contribution statement

**Karim Zahed:** Formal analysis, Methodology, Writing – original draft. **Carl Markert:** Formal analysis, Investigation, Writing – review & editing. **Farzan Sasangohar:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – review & editing.

## Declaration of Generative AI and AI-assisted technologies in the writing process

None were used.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

**Table A.1**
Engagement criteria to achieve medals

| Feature | Medal | | |
|---|---|---|---|
| | Bronze | Silver | Gold |
| Relaxation Media | Use 1 sound & 1 video | Use 5 sounds & 5 videos | Use 10 sounds & 10 videos |
| Breathe | Complete 1 exercise | Completes 5 exercises | Completes 10 exercises |
| Focus | Complete 1 exercise | Complete 5 exercises | Complete 10 exercises |
| Motivation | Read 5 quotes 1/day for the first week | Read 25 quotes 1/day for the first 5 weeks | Read 50 quotes 1/day for the whole 10 weeks |
| Journal | Complete 1 entry | Complete 5 entries | Complete 10 entries |
| Calendar | Sync school schedule w/calendar | Open the app 5 times 1/day for the first 5 weeks | Open the app 10 times 1/day for the whole 10 weeks |
| Lists | Create 1 list | Create 5 lists | Create 10 lists |
| Education | Read 1 article & 1 video | Participate in half of the coaching plan | Complete the full coaching plan |
| Self-Assessment | Complete 1 of each assessment | Complete 3 of each assessment | Complete 5 of each assessment |

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