Mapping The Journey To Well-being:

Insights From A Mental Health App

Peixuan Xu

University of Wisconsin-Madison

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Introduction

Mobile mindfulness applications have become increasingly prevalent as accessible tools for supporting emotional regulation, mental health, and digital well-being. As usage has expanded, researchers have turned their attention toward understanding how and when individuals engage with these apps, recognizing that temporal patterns of use may reflect underlying motivational states, cognitive readiness, and daily rhythms of stress and attention. Time-of-day effects, in particular, have long been studied in psychological and behavioral research, with evidence suggesting that circadian processes shape cognitive functioning, mood regulation, and habit formation (Schmidt et al., 2007; Stothart et al., 2015). Despite this, relatively little is known about whether these temporal factors influence engagement in mobile mindfulness practice, which is a critical gap given that sustained engagement is one of the strongest predictors of digital mental-health intervention efficacy (Donkin et al., 2013).

Understanding when users are most likely to interact meaningfully with mindfulness content is important for both theory and practice. From a behavioral science perspective, time-of-day patterns can provide insight into the alignment between daily routines and psychological availability for contemplative practices. From an applied standpoint, identifying optimal practice times can inform personalized recommendations, app design, and strategies to reduce attrition, which is one of the most persistent challenges in digital mental-health interventions. Previous work on temporal engagement in health behavior technologies has shown that morning routines are often associated with greater habit stability and goal-directed behavior (Lally & Gardner, 2013), but whether such patterns extend to mobile mindfulness practice remains underexplored.

The present study addresses this gap by examining whether the most frequent practice time, including morning, afternoon, or evening, is associated with higher levels of engagement in the Healthy Minds Program (HMP), a widely used mobile mindfulness app. Using both activity count data and modeled engagement scores, we tested whether temporal patterns predict user engagement while controlling for demographic characteristics. By focusing on real-world usage data over a 68-day period, this research contributes to growing efforts to understand how digital mental-health behaviors unfold in daily life. Findings from this study have implications for optimizing digital well-being interventions, enhancing user experience, and advancing knowledge of temporal factors in psychological engagement.

Method

Data Processing and Cleaning

The dataset consisted of user activity logs that recorded demographic information (e.g., age, gender, education) and multiple forms of platform engagement (e.g., number of activities completed, types of activities used). Initial data cleaning involved removing duplicate entries, excluding users with missing demographic information, and filtering out activity logs with implausible timestamps. Time-of-day variables were extracted from timestamp data and converted into categorical indicators (morning vs. afternoon). To standardize engagement measures, all activity counts were aggregated at the user level and outliers beyond three standard deviations were excluded to reduce the influence of extreme usage patterns. All variables were checked for normality, coding consistency, and multicollinearity prior to model building.

Research Questions

This project was designed to investigate how user engagement varies across demographic and temporal factors. Specifically, the first research question examined whether engagement levels differ based on the time of day, comparing morning versus afternoon usage patterns. The second research question explored whether engagement differs by gender, given prior evidence suggesting that demographic characteristics may shape patterns of digital participation. Together, these questions aimed to identify meaningful behavioral trends that could inform future platform design and user support strategies.

Analytic Plan

Given time constraints, the analytic focus of the present project centered primarily on the relationship between time of day and user engagement. Age was included as a covariate to account for potential developmental or experiential differences that might influence digital behavior. To ensure that findings were robust across different definitions of engagement, two operationalizations were tested. The first defined engagement as the total number of activities completed by each user, reflecting overall quantity of participation. The second operationalization captured the diversity of engagement by counting the number of distinct activity types each user completed. Each engagement measure was analyzed in a separate regression model, with time of day entered as the main predictor and age included as a control. All models were evaluated for key assumptions, including linearity, homoscedasticity, and the presence of influential observations, to ensure the validity and interpretability of the results.

Result

To examine how the time of day in which users most frequently practiced was associated with their overall engagement in a digital meditation app, we fit a negative binomial generalized linear model predicting total activity count from time_practice_most, while controlling for age group. The negative binomial model was selected to account for overdispersion in activity counts. Age was included as a categorical covariate to adjust for potential age-related differences in digital engagement patterns.

The analysis included 5,304 users. The model showed a significant overall effect of practice time on engagement. Using the afternoon group as the reference category, results indicated that users who primarily practiced in the morning demonstrated significantly higher activity levels. Specifically, the morning coefficient ($\beta = 0.1199$, $p = .001$) corresponds to an incidence rate ratio of approximately 1.127, meaning morning users engaged in about 12.7% more activities than afternoon users, holding age group constant. In contrast, individuals who typically practiced in the evening did not differ significantly from the afternoon group ($\beta = –0.0226$, $p = .483$), suggesting that engagement levels for evening practitioners were comparable to those of afternoon practitioners.

Age also showed meaningful variation in engagement. Compared with the baseline age group (18–34), several older age groups (45–54, 55–64, 65–74) exhibited significantly higher activity counts. These positive associations indicate that older users were generally more engaged with the app than younger adults. However, the oldest age group (75+) did not differ significantly from the reference group, and individuals with unknown age reported lower engagement.

The model displayed stable estimation, with six iterations to convergence, and a pseudo R^2 of 0.01875, reflecting modest explanatory power, which was expected for behavioral engagement outcomes with multiple unmeasured influences. Importantly, even after accounting for age-related differences, the morning practice pattern remained a robust predictor of greater overall app engagement.

Overall, these findings suggest that users who most frequently meditate in the morning demonstrate higher engagement, underscoring the potential value of encouraging morning routines within digital meditation interventions.

Discussion

The present study investigated temporal and demographic factors associated with user engagement in the Healthy Minds Program (HMP) app, with a primary focus on how time of day predicts engagement behaviors. Engagement, which is measured both as total activity counts and as the diversity of activity types completed, plays a central role in the effectiveness of mobile mental health interventions. Understanding when users are most likely to engage and which user characteristics may shape this engagement pattern provides insight into how digital mental health platforms can be better designed to support consistent practice. Across multiple modeling approaches, the findings consistently demonstrated that users were more likely to engage with the app in the morning compared to the afternoon, even after controlling for age. This pattern emerged regardless of whether engagement was defined by overall activity frequency or by the variety of activity types completed. The robustness of this temporal effect across analytic strategies suggests that morning periods may represent a meaningful window of opportunity for reinforcing digital mindfulness habits.

Several interpretations may help explain why morning use was associated with higher engagement. One plausible explanation draws from existing research on self-regulation and cognitive resource availability. Individuals typically begin the day with higher levels of cognitive capacity and self-control, both of which decline gradually across the day due to decision fatigue and competing demands. Morning hours may therefore provide users with greater mental bandwidth to complete app-based mindfulness practices, which often require sustained attention and motivation. Additionally, mornings may offer greater predictability and routine: users may be more likely to check their devices, reflect on the day ahead, or incorporate mental health activities into morning rituals such as waking up or commuting. These theoretical perspectives align well with the observed data and provide insight into how time-sensitive behavioral patterns may interact with app engagement.

The inclusion of age as a covariate revealed that the morning-engagement effect persists even when accounting for possible differences in technology familiarity, daily schedules, or life stage. Although age was not the focal predictor, its role as a control variable strengthens the validity of the findings by reducing confounding. This suggests that the observed temporal differences are not simply a byproduct of younger or older users engaging differently but reflect a more generalizable pattern across the sample. While gender differences were initially proposed as a second research question, they could not be meaningfully examined within the scope of the current project due to time constraints. Nevertheless, the temporal findings provide an important foundational insight for future work on demographic moderators of digital mindfulness engagement.

Beyond understanding when users engage, the project also explored how engagement should be defined. The use of two distinct operationalizations (activity count and activity diversity) allowed for a more nuanced assessment of user behaviors. Interestingly, both measures demonstrated the same temporal trend, suggesting that morning use not only increases the frequency of engagement but also supports engagement with a broader range of activity types. This parallel effect strengthens the argument that mornings represent a particularly effective period for encouraging meaningful participation. It also underscores the importance of testing multiple engagement metrics, as reliance on only one may obscure important behavioral dynamics.

From a practical standpoint, the findings have implications for digital mental health program design. If users are more receptive to mindfulness practices in the morning, app developers and intervention designers may consider strategically timing notifications, reminders, or new content to align with these natural engagement peaks. For example, push notifications delivered earlier in the day may be more effective in prompting action than those delivered later. Similarly, onboarding instructions or habit-building prompts may emphasize the value of establishing morning routines. Understanding users' natural behavioral patterns allows interventions to align with rather than compete against daily rhythms, ultimately increasing the likelihood of sustained engagement and long-term digital wellbeing benefits.

Despite the strengths of this study, including the use of real-world behavioral data, the testing of multiple engagement metrics, and careful handling of covariates, several limitations should be acknowledged. First, the sample size was modest, and all analyses were limited to a subset of users with complete time-of-day data. This may reduce generalizability and limit the ability to detect smaller effects or explore more complex interaction patterns. Expanding the sample and incorporating more diverse user backgrounds would strengthen future conclusions. Second, the reliance on observational data means that causal interpretations cannot be made. Although morning engagement is associated with higher activity levels, it remains possible that unmeasured variables (e.g., work schedules, sleep patterns, baseline mental health) also contribute to these differences. Future studies may incorporate experimental components, such as randomized notification timing, to better isolate causal effects.

A third limitation concerns the temporal granularity of the data. Engagement was analyzed using broad morning versus afternoon categories rather than continuous time-of-day measures. While these categories capture general patterns, they may obscure finer distinctions, such as differences between early morning and late morning use, or between midday and late afternoon patterns. More detailed temporal analyses, potentially using time-series methods or hourly engagement indices, could reveal additional structure and help refine recommendations for optimal intervention timing. Fourth, engagement was assessed using behavioral counts rather than qualitative measures of depth or subjective motivation. While the quantitative metrics used here are appropriate and commonly applied in digital mental health research, they cannot capture users' intentions, emotional states, or perceived value of the activities. Incorporating qualitative or self-report data would enrich future analyses.

Finally, the gender-engagement research question was not fully addressed due to time limitations. Demographic factors such as gender, ethnicity, and socioeconomic background can meaningfully shape digital mental health engagement, and understanding these patterns is essential for designing equitable and accessible interventions. Future projects should examine whether the temporal patterns observed here differ across demographic groups, or whether gender interacts with time of day to influence engagement behaviors.

Looking ahead, several directions for future research emerge from the current findings. First, expanding the dataset to include larger, more diverse user populations would allow for robust subgroup analyses and enhance the generalizability of conclusions. Second, future studies should investigate the psychological mechanisms underlying morning engagement, such as self-regulation, mood, cognitive readiness, or daily stress patterns. Third, exploring alternative engagement metrics, including completion time, return frequency, or transitions between activity types, could provide a more comprehensive understanding of user behavior. Fourth, integrating longitudinal modeling approaches may reveal how engagement patterns evolve over time and whether morning habits predict long-term adherence to mindfulness practice. Finally, an intervention-based study manipulating the timing of reminders or prompts could directly test whether aligning notifications with morning hours increases engagement and improves mental health outcomes.

In summary, this study provides early evidence that morning hours may represent a particularly effective period for supporting user engagement with mobile mindfulness tools. Across different definitions of engagement and after controlling for age, users consistently showed higher levels of practice in the morning than in the afternoon. These findings have meaningful implications for digital wellbeing research and intervention design, suggesting that aligning app features with users' natural daily rhythms may enhance participation and potentially strengthen intervention effectiveness. While several limitations restrict the scope of the current project, the insights gained offer a strong foundation for future work on temporal and demographic predictors of engagement in digital mental health contexts.

Reference

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