Integrated Health Belief and User Engagement Model for Physical Activity Apps

Nur Farahin Mohd Johari[1], Nazlena Mohamad Ali[2], Mohamad Hidir Mhd Salim[3]*
Institute of Visual Informatics, National University of Malaysia, Bangi, Selangor, Malaysia[1, 2, 3]
Faculty of Computer and Mathematical Sciences, UiTM Cawangan Melaka Kampus Jasin, Melaka, Malaysia[1]

***Abstract*—Physical activity applications support monitoring, motivating, and sustaining healthy behavior, yet long-term engagement remains challenging. This study validates an integrated Health Belief Model and User Engagement Model for explaining behavior change among physical activity application users. Survey data from 423 users were analyzed using Partial Least Squares Structural Equation Modeling, followed by a four-week Strava study involving 17 participants and post-usage interviews. The results showed that Healthy Behavior Adoption and Health Technology Engagement significantly influenced behavior change, with technology engagement exerting the stronger effect. Perceived usability and reward factors were the strongest predictors of technology engagement, while self-efficacy and objective barriers were the strongest predictors of healthy behavior adoption. Focused attention and cues to action were not significant. Real-world usage and interview findings supported the model by showing that usability, meaningful feedback, and perceived progress were more influential than continuous attention or repeated reminders in supporting sustained physical activity behavior.**

***Keywords*—Mobile health; physical activity applications; health belief model; user engagement model; behavior change; technology engagement**

I. Introduction

Physical inactivity remains a public health challenge despite various campaigns and interventions being implemented. The prevalence of insufficient physical activity has been reported to increase from 26.4% in 2010 to 31.3% in 2022, indicating that awareness of the importance of physical activity has not necessarily led to sustained behavioral changes [1]. In this context, mobile health applications, or mHealth, are increasingly used to support activity monitoring, goal setting, performance feedback, and the formation of an active lifestyle.

Although mHealth applications have the potential to increase physical activity, their effectiveness is often limited by decreased engagement and discontinuation of use after the initial phase. Users may stop using the application due to time constraints, usability issues, decreased motivation, or the perception that the application is no longer needed [2], [3]. Additionally, frequent use of the application does not necessarily reflect meaningful engagement or actual behavior change. Therefore, the evaluation of mHealth applications should take into account not only user perceptions but also usage experiences and behavioral data in real contexts [4], [5].

Previous studies typically explain behavioral changes from the perspective of health psychology or technology engagement separately. The Health Belief Model (HBM) explains how perceptions of benefits, barriers, severity, self-efficacy, and cues to action influence individual health decisions [6], [7]. However, the HBM does not explain the user interaction experience with digital applications. On the other hand, the User Engagement Model (UEM) emphasizes focused attention, usability, aesthetic appeal, and reward factors in shaping the technology usage experience [8], [9], but it pays less attention to health beliefs that drive physical activity behavior.

To address this gap, this study integrates HBM and UEM into a single model of user behavior change for physical activity applications. This model proposes two parallel mechanisms: "Healthy Behavior Adoption," shaped by health beliefs, and "Health Technology Engagement," influenced by the experience of using the application. Both mechanisms are expected to drive changes in user behavior. This approach allows for an understanding of behavioral change through a combination of health motivation and technology experience, rather than relying on a single theoretical perspective.

This study aims to validate the integrated HBM-UEM model using PLS-SEM, based on data from 423 users of physical activity applications. The model was further evaluated in a real-world usage context through a four-week study of Strava usage involving 17 participants, followed by post-usage interviews. The study contributes to the fields of mHealth and human-computer interaction by combining statistical validation, real-world usage data, and user experience to explain how health beliefs and technology engagement jointly support behavioral changes regarding physical activity.

The theoretical contribution of this study indicates that behavioral change in physical activity applications stems from two complementary mechanisms, as it cannot be fully explained by a single perspective. While existing studies based on the Health Belief Model (HBM) are useful for explaining healthy behaviors in terms of perceived barriers and risks, they offer limited insight into how users evaluate and sustain engagement with digital applications. Conversely, engagement-based models account for factors such as interaction quality, usability, attention, aesthetic appeal, and rewards, yet they fail to consider the health-related beliefs that drive physical activity adequately. By integrating HBM and UEM, this study extends prior research by distinguishing between Healthy Behavior Adoption, which represents psychological readiness, and Health Technology Engagement, which represents users' digital experience. This dual-pathway structure enables a more comprehensive explanation of behavioral change in mobile health (mHealth) physical activity applications, highlighting that users require

*Corresponding author.

both the psychological motivation to remain active and the technological support to sustain the app-driven behavior.

II. Related Work

A. mHealth Applications and Changes in Physical Activity Behavior

Mobile health (mHealth) applications are increasingly being used to support physical activity through features such as step and distance monitoring, goal setting, performance feedback, and progress tracking. Previous studies indicate that the use of mHealth applications can increase step counts and the duration of physical activity, particularly during short-term interventions [10]. However, these effects do not necessarily persist after the intervention ends. Users also frequently reduce or discontinue app usage after the initial phase due to usability issues, the need for manual input, time constraints, subscription costs, and declining motivation [11], [12].

User engagement in mHealth encompasses behavioral and psychological dimensions. The behavioral dimension refers to the frequency of use, number of sessions, and duration of interaction, while the psychological dimension involves motivation, attention, satisfaction, and perceived value from using the application [13]. Although higher engagement is often associated with increased physical activity, frequent use of the application does not necessarily result in behavioral change if the interaction does not hold meaning for the user [4]. Therefore, the evaluation of physical activity applications needs to consider user experience and actual behavior, not just intention or frequency of use.

B. Health Belief Model in the Context of mHealth

The Health Belief Model HBM explains that individual health actions are influenced by beliefs about health risks, the benefits of actions, barriers faced, self-efficacy, and cues to action [6], [7]. In physical activity studies, perceived benefits, perceived barriers, and self-efficacy are often identified as important factors influencing an individual's decision to initiate or maintain active behavior [14], [15].

Recent mHealth and digital health studies have continued to apply HBM to explain users' adoption of health applications, preventive health behavior, exercise participation, and technology-supported self-management. For example, Alharbi et al. [16] applied the HBM to examine health mobile app adoption and found that perceived benefits and self-efficacy were important predictors of behavioral intention, while perceived barriers and cues to action were not significant. Nasution et al. [17] also used HBM constructs to guide the development of a mobile health application for breast examination awareness, showing that the model remains relevant for structuring app-based health promotion content. In the context of physical activity, Faghih et al. [18] demonstrated the usefulness of HBM-based training and social support in promoting physical activity. However, studies on continuous mHealth use also indicate that sustained engagement is influenced by usability, feedback, personalization, and interaction experience [19]. Therefore, although HBM remains valuable for explaining health-related beliefs and readiness to act, it needs to be complemented by a technology engagement perspective when studying physical activity applications.

In the context of mHealth, HBM is used to explain how users assess the benefits of the application, usage barriers, and self-efficacy to engage in health behaviors. Applications that provide monitoring, goal setting, and progress visualization have the potential to enhance users' self-efficacy. However, users who understand the benefits of an application can still stop using it when the interaction experience is unsatisfactory, the content becomes repetitive, or the application no longer fits their daily routine [19]. This indicates that HBM is more effective in explaining health motivations and decisions, but less effective in explaining the continuous experience of technology use.

Additionally, HBM was originally developed to explain health behaviors that are more episodic in nature. Therefore, its ability to explain behaviors that require long-term commitment, such as physical activity and continuous app usage, still has limitations [18]. In a digital environment, health trust needs to be complemented by factors that explain how users experience and evaluate their interactions with the application.

III. Methodology

A. Study Design

This study employs a multi-phase mixed-methods design to validate the integration model of the Health Belief Model and the User Engagement Model. The quantitative component is used as the primary method to evaluate the measurement model and the structural model, while actual application usage data and user interviews are used to provide contextual validation and explanation for the statistical findings. This design allows the model to be evaluated through three forms of evidence, namely user perception, actual usage behavior, and user subjective experience.

Specifically, the study involves three stages. The first stage is the empirical validation of the model using a questionnaire and Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. The second stage involves a longitudinal study of the use of the Strava application over four weeks. The third stage involves post-usage interviews to explain the behavior patterns and experiences of the participants. The Strava study and interviews were not used to re-estimate the structural model, but as behavioral and contextual validation of the relationships identified through PLS-SEM.

B. Participants and Data Collection of the Questionnaire

The target population consists of adult users aged 18 and above who own a smartphone and have either used or are currently using at least one physical activity application. Purposive sampling was used to ensure that respondents had relevant experience to evaluate the app features and behavioral changes. From the responses received, 423 respondents who met the participation criteria were used in the final analysis.

The research instrument contains items that measure the constructs of HBM, UEM, Healthy Behavior Adoption (HBA), Health Technology Engagement (HTE), and behavior change. The HBM construct includes perceived benefits, objective barriers, subjective barriers, self-efficacy, perceived severity, and cues to action. The UEM construct, on the other hand, consists of focused attention, perceived usability, aesthetic appeal, and reward factors. All items were adapted from instruments used in previous studies and measured using a five-point Likert scale.

The questionnaire was developed based on established measures of HBM, user engagement, technology engagement, and behavior change. Each construct was operationalized according to its theoretical meaning in the context of physical activity applications. Perceived benefits measured users' beliefs regarding the usefulness of physical activity applications in improving health and activity behavior. Objective barriers captured external constraints such as time, cost, access, and environmental limitations, while subjective barriers captured internal concerns such as lack of confidence, low motivation, and perceived difficulty. Self-efficacy measured users' perceived ability to engage in physical activity with the support of the application. Perceived severity assessed users' awareness of the consequences of physical inactivity, while cues to action measured prompts, reminders, notifications, and social triggers that may encourage activity.

For the UEM constructs, focused attention measured the extent to which users were absorbed in interacting with the application, perceived usability assessed ease of use and clarity of interaction, aesthetic appeal measured visual attractiveness and interface presentation, and reward factors captured the role of achievements, feedback, badges, and progress indicators. Healthy Behavior Adoption represented users' intention and readiness to adopt physical activity behavior, while Health Technology Engagement represented meaningful engagement with the application. Behavior change measured perceived changes in physical activity behavior after using the application. All items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. The adapted items were reviewed for contextual suitability before data collection.

C. PLS-SEM Analysis

Survey data were analyzed using SmartPLS through two main stages. The first stage involves the assessment of the measurement model. Internal reliability is assessed using Cronbach's alpha and composite reliability values, while convergent validity is evaluated through the Average Variance Extracted (AVE) value. Discriminant validity is assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT).

The second stage involves the evaluation of the structural model to test the relationships between constructs. In addition to the assessment of path coefficients, the structural model was evaluated using collinearity statistics, model fit, and bootstrapping results. Variance inflation factor (VIF) values were examined to determine whether multicollinearity was present among predictor constructs. Bootstrapping was conducted to obtain t-values, p-values, and confidence intervals for each hypothesized relationship. These procedures were used to ensure that the structural paths were statistically reliable and that the model validation was not based solely on path coefficients. This analysis includes the examination of collinearity, path coefficients, t-values, and p-values through the bootstrapping procedure. The explanatory and predictive capabilities of the model are evaluated using the R^2 coefficient of determination, f^2 effect size, and Q^2 predictive value. PLS-SEM was chosen because it is suitable for models involving many latent constructs, is prediction-oriented, and does not require strict assumptions of data normality.

The health-belief pathway explains HBA through perceived benefits, objective barriers, subjective barriers, self-efficacy, perceived severity, and cue to action. The technology-engagement pathway explains HTE through focused attention, perceived usability, aesthetic appeal, and reward factors. The structural relationships are expressed as follows:

$$HBA = \beta_1 PB + \beta_2 POB + \beta_3 PSB + \beta_4 SE + \beta_5 PS + \beta_6 CTA + \zeta_1, \quad (1)$$

$$HTE = \beta_7 FA + \beta_8 PU + \beta_9 AE + \beta_{10}\, RW + \zeta_2$$

$$BC = \beta_{11} HBA + \beta_{12}\, HTE + \zeta_3$$

where, β represents the path coefficients and ζ represents the residual terms. These relationships were estimated using PLS-SEM.

D. Study of Actual Strava Usage

After the empirical validation of the model, a longitudinal case study was conducted to assess whether the behavioral change mechanisms in the model could be observed in actual app usage. This study involved 17 participants aged between 18 and 35 years who were physically inactive, owned a smartphone, and had never used the Strava application.

Before participating in the study, the participants underwent screening using the International Physical Activity Questionnaire–Short Form (IPAQ-SF), the Stages of Change Questionnaire, and the Physical Activity Readiness Questionnaire (PAR-Q+). This screening aims to identify the initial level of activity, readiness to change, and the suitability of participants to engage in physical activity.

Participants are asked to use Strava for four weeks and engage in at least three physical activity sessions per week, with a minimum duration of 30 minutes for each session. Strava was chosen because it provides an objective record related to the number of sessions, duration, distance, frequency, and consistency of activities. Participants' log data were analyzed to identify weekly usage patterns, adherence to targets, and early changes in physical behavior. This study aims to provide real-world validation rather than statistical generalization, given the small sample size.

The Strava substudy was not intended to statistically represent the larger survey sample or to re-estimate the structural model. Instead, it served as a contextual and behavioral validation component to examine whether selected mechanisms identified in the PLS-SEM model could be observed in actual application use. The smaller and more homogeneous sample allowed the study to monitor real-world app usage consistently over four weeks. Therefore, the triangulation was interpreted as convergent contextual evidence rather than direct sample equivalence between the survey and longitudinal components.

E. Post-Usage Interview

Semi-structured interviews were conducted after the four-week Strava usage period to understand participants' experiences with the application and to explain the quantitative findings. The interview questions focused on users' motivation to be physically active, perceived benefits and barriers, experience with Strava features, perceived usefulness of feedback and rewards, attention during app use, reminders, and perceived behavior change. Each interview was conducted after the completion of the usage study and was guided by an interview protocol aligned with the HBM and UEM constructs.

The interview data were analyzed using thematic analysis. The analysis involved transcription of participants' responses, repeated reading to obtain familiarity with the data, initial coding based on meaningful statements, grouping of related codes into themes, and interpretation of themes in relation to the HBM-UEM constructs. A deductive approach was used because the coding was guided by the constructs in the integrated model, while inductive interpretation was applied to identify contextual explanations that emerged from participants' experiences. The themes were then compared with the PLS-SEM results and Strava usage patterns to determine whether the qualitative findings supported, contradicted, or extended the quantitative results.

F. Data Integration

To gain further insight into the quantitative data findings, data triangulation was conducted to deepen the understanding of the results. This process involved triangulating the quantitative data with qualitative data derived from actual usage patterns and interviews. This triangulation is crucial for understanding the actual situations and user behaviors regarding the use of physical activity applications.

IV. Results

A. Measurement Model Assessment

The assessment of the measurement model shows that all constructs meet the established levels of reliability and validity. The Cronbach's alpha and composite reliability values for all constructs exceed 0.70, while the Average Variance Extracted (AVE) values exceed 0.50. These findings indicate that the measurement items have satisfactory internal consistency and convergent validity. Table I presents the summary of the measurement model assessment, including indicator loading range, Cronbach's alpha, composite reliability, and AVE values for each construct.

The measurement model demonstrated acceptable reliability and convergent validity. Cronbach's alpha and composite reliability values exceeded the recommended threshold of 0.70 for all constructs, while AVE values were above 0.50. Most indicator loadings exceeded 0.70. Several items, including HBA8, PSB1, PU2, and SE1, recorded lower loadings; however, they were retained because the AVE and composite reliability values remained acceptable and the items were theoretically relevant to their respective constructs.

Discriminant validity was also confirmed through the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). All HTMT values are below the threshold of 0.90, with the highest value being 0.799 between Health Technology Engagement (HTE) and behavioral change. Therefore, each construct in the model can be empirically distinguished from the other constructs.

TABLE I. MEASUREMENT MODEL ASSESSMENT

Construct	Item	Loading Range	CA	CR	AVE
BC	BC1-BC7	0.607–0.877	0.904	0.910	0.638
HTE	HTE1-HTE6	0.713–0.933	0.940	0.950	0.775
HBA	HBA1-HBA8	0.313–0.849	0.891	0.915	0.590
EA	AE1-AE3	0.872–0.932	0.897	0.937	0.826
FA	FA1-FA3	0.834–0.917	0.843	0.940	0.752
PU	PU1-PU3	0.643–0.944	0.714	0.780	0.648
RW	RW1-RW3	0.900–0.933	0.903	0.906	0.837
CTA	CTA1-CTA3	0.751–0.912	0.788	0.841	0.701
PB	PB1-PB3	0.909–0.951	0.923	0.952	0.865
POB	POB1-POB4	0.924–0.979	0.965	0.967	0.905
PS	PS1-PS2	0.766–0.954	0.700	0.910	0.749
PSB	PSB1-PSB3	0.470–0.969	0.702	0.969	0.563
SE	SE1-SE3	0.691–0.879	0.713	0.755	0.636

[a] Note: CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, BC = Behaviour Change; HTE = Health Technology Engagement; HBA = Healthy Behaviour Adoption; AE = Aesthetic Appeal; FA = Focused Attention; PU = Perceived Usability; RW = Reward Factor; CTA = Cue to Action; PB = Perceived Benefits; POB = Perceived Objective Barriers; PS = Perceived Severity; PSB = Perceived Subjective Barriers; SE = Self-Efficacy.

TABLE II. DISCRIMINANT VALIDITY SUMMARY

Criterion	Result	Interpretation
Fornell–Larcker criterion	The square root of AVE for each construct was higher than its correlations with other constructs.	Discriminant validity was established.
HTMT	All HTMT values were below 0.90; the highest HTMT value was 0.799 between HTE and BC.	Discriminant validity was established.
Cross-loading	All indicators loaded highest on their intended constructs compared with other constructs.	No critical cross-loading issue was detected.

Discriminant validity was confirmed using the Fornell–Larcker criterion, HTMT, and cross-loading assessment (Table II). The Fornell–Larcker results showed that each construct shared higher variance with its own indicators than with other constructs. All HTMT values were below 0.90, with the highest value of 0.799 between HTE and BC. The cross-loading assessment also showed that each indicator loaded highest on its assigned construct, indicating no critical overlap among indicators.

B. Model Evaluation: Structural Model Assessment

The results of the structural model analysis indicate that 10 out of the 12 tested relationships are significant. Table III summarizes the path coefficient results for the HBM–UEM integration model. Table III shows that 10 of the 12 hypothesized relationships were supported, with HTE exerting the strongest effect on behaviour change.

$$BC = 0.230(HBA) + 0.653(HTE) \qquad (2)$$

TABLE III. STRUCTURAL MODEL PATH COEFFICIENTS AND HYPOTHESIS TESTING RESULTS

Relationship	β	t-Value	p-Value	f^2	Result
HTE → BC	0.653	18.447	<0.001	0.883	Supported
HBA → BC	0.230	4.890	<0.001	0.110	Supported
AE → HTE	0.114	3.154	0.002	0.005	Supported
FA → HTE	0.064	1.258	0.208	0.027	Not Supported
PU → HTE	0.438	10.991	<0.001	0.344	Supported
RW → HTE	0.358	8.193	<0.001	0.139	Supported
CTA → HBA	0.098	1.686	0.092	0.052	Not Supported
PB → HBA	0.200	5.717	<0.001	0.082	Supported
POB → HBA	0.315	10.399	<0.001	0.253	Supported
PS → HBA	0.235	7.002	<0.001	0.117	Supported
PSB → HBA	0.147	4.829	<0.001	0.028	Supported
SE → HBA	0.320	9.527	<0.001	0.270	Supported

[b] Note: BC = Behavior Change; HTE = Health Technology Engagement; HBA = Healthy Behavior Adoption; AE = Esthetic Appeal; FA = Focused Attention; PU = Perceived Usability; RW = Reward Factor; CTA = Cue to Action; PB = Perceived Benefit; POB = Objective Barrier; PS = Perceived Severity; PSB = Subjective Barrier; SE = Self-Efficacy.

Based on the estimated path coefficients, the final behavior change equation is expressed in Eq. (2), indicating that technology engagement exerted a stronger effect than healthy behavior adoption.

HTE is the strongest predictor of behavior change with a β value of 0.653, while HBA also has a positive and significant influence with a β value of 0.230. In the technology pathway, perceived usability is the strongest predictor of HTE (β = 0.438), followed by reward factors (β = 0.358) and aesthetic appeal (β = 0.114). Focused attention does not show a significant relationship with HTE (β = 0.064, p = 0.208).

In the health belief pathway, self-efficacy is the strongest predictor of HBA (β = 0.320), followed by objective barriers (β = 0.315), perceived severity (β = 0.235), perceived benefits (β = 0.200), and subjective barriers (β = 0.147). The cue to action does not have a significant influence on HBA (β = 0.098, p = 0.092).

C. Model's Explanatory Power and Predictive Relevance

The model recorded an R^2 value of 0.665 for HBA, 0.538 for HTE, and 0.613 for behavioral change. This shows that the HBM construct explains 66.5% of the variation in HBA, the UEM construct explains 53.8% of the variation in HTE, while HBA and HTE together explain 61.3% of the variation in behavioral change.

Effect size analysis shows that HTE has a large effect on behavioral change, with $f^2 = 0.883$, while HBA has a small effect, with $f^2 = 0.110$. In the technology pathway, perceived ease of use has a moderate effect on HTE ($f^2 = 0.344$), followed by the reward factor ($f^2 = 0.139$). In the HBM path, self-efficacy ($f^2 = 0.270$) and objective barriers ($f^2 = 0.253$) show a moderate effect on HBA.

All endogenous constructs also recorded Q^2 values exceeding zero, namely 0.382 for HBA, 0.412 for HTE, and 0.375 for behavioral change. This result (Table IV) shows that the model has satisfactory predictive relevance.

TABLE IV. MODEL EXPLANATORY POWER, PREDICTIVE RELEVANCE AND COMMON METHOD BIAS

Assessment	Construct / Test	Value	Interpretation
R^2	BC	0.613	Substantial
R^2	HTE	0.538	Substantial
R^2	HBA	0.665	Substantial
Q^2	BC	0.375	High predictive relevance
Q^2	HTE	0.412	High predictive relevance
Q^2	HBA	0.382	High predictive relevance
Common method bias	Harman's single-factor test	30.61%	Below 50%; low risk of common method bias

The model demonstrated satisfactory explanatory and predictive capability. The R^2 values indicated substantial explanatory power for BC, HTE, and HBA, while Q^2 values above zero confirmed predictive relevance. Common method bias was assessed using Harman's single-factor test. The first factor explained 30.61% of the total variance, which is below the 50% threshold, indicating that common method bias was unlikely to be a serious concern.

D. Pattern of Strava Usage in Real Context

The real usage study involved 17 participants, consisting of eight men and nine women aged between 18 and 23 years. The majority of the participants were students. Throughout the four weeks, a total of 55 sessions were recorded in Week 1, 52 sessions in Week 2, 58 sessions in Week 3, and 48 sessions in Week 4. Table V shows that participants maintained approximately three activity sessions per week, with the highest activity recorded in Week 3.

TABLE V. WEEKLY STRAVA USAGE AND PHYSICAL ACTIVITY STATISTICS

Metric	Week 1	Week 2	Week 3	Week 4
Number of sessions/week	3.18 ± 1.01	2.76 ± 1.30	3.24 ± 1.75	2.82 ± 1.51
Active minutes/week	112.34 ± 75.92	99.52 ± 66.70	146.20 ± 106.65	105.11 ± 65.23
Average minutes/session	33.59 ± 16.86	35.08 ± 18.46	45.11 ± 22.81	39.43 ± 22.23

[c] Note: Values are presented as mean ± standard deviation.

The average number of sessions remained nearly three sessions per week throughout the study. The highest activity level was recorded in Week 3, with an average of 3.24 sessions and 146.20 active minutes per week. However, activity decreased again in Week 4 to 2.82 sessions and 105.11 minutes. The percentage of participants who met the session and activity duration targets reached its highest level in Week 3, at 64.71%, and remained at 58.82% in Week 4. This pattern shows that behavioral changes do not occur linearly, but rather fluctuate according to time, commitment, and the daily circumstances of the participants.

E. Post-Usage Interview Findings

Post-usage interview findings revealed several themes aligned with the HBM and UEM constructs. Participants were aware of the dangers of physical inactivity and the benefits of an active lifestyle, which correspond to the constructs of perceived severity and perceived benefits.

However, participants also acknowledged that time constraints, commitments, weather conditions, and other factors served as major barriers to remaining active. Participants may have lacked confidence in their ability to engage in physical activity during unfavorable weather (such as rain or excessive heat) or were unaware that they could perform simple physical activities without disrupting their daily commitments. App-based recommendations and personalization are crucial to ensuring that participants do not allow these constraints to deter them from engaging in physical activity.

From the UEM perspective, participants generally found Strava easy to use, noting its organized and uncomplicated interface. Features such as maps, distance, duration, and progress tracking helped participants evaluate their performance and foster a sense of achievement. However, the impact of digital rewards varied; some participants valued medals and achievements, while others paid little attention to them.

Participants also explained that they did not need to constantly monitor the app while exercising. The app was simply activated before the activity and allowed to run in the background. This finding aligns with the non-significant relationship observed between focused attention and HTE. Some participants continued their physical activity even as their usage of Strava declined, indicating that reduced interaction with the app did not necessarily mean the behavioral change had ceased.

F. Integration of Findings

Overall, the PLS-SEM findings, Strava data, and interviews support the two-path structure in the HBM–UEM integration model. The HBM pathway shows that perceived benefits, barriers, severity, and self-efficacy shape HBA, while the UEM pathway shows that usability, rewards, and aesthetics shape HTE. Both paths influence behavior change, but the technology engagement path shows a stronger effect.

The findings of actual usage also provide an explanation for the two insignificant relationships. Focused attention is not required continuously because Strava operates passively during the activity. The cues to action are also insufficient to form HBA without internal motivation, perceived benefits, and self-efficacy. Therefore, the triangulation of findings indicates that behavioral changes in the application of physical activities are influenced by a combination of psychological readiness and practical, meaningful technological experience.

The qualitative findings did not merely confirm the statistical results but helped explain why certain relationships were stronger or weaker in actual use. For example, interviews clarified why perceived usability strongly influenced technology engagement: participants valued Strava because it required minimal effort during activity while still producing meaningful feedback after exercise. The interviews also explained why focused attention was not significant, as users did not need to continuously interact with the app during physical activity. Similarly, the weak role of cues to action was explained by participants' reliance on personal goals, confidence, and progress feedback rather than generic reminders. These insights suggest that sustained behaviour change in physical activity apps depends less on continuous screen-based attention and more on low-effort tracking, meaningful feedback, and alignment with users' daily routines.

V. Discussion

The findings from PLS-SEM, actual Strava usage, and interviews indicate that behavioral change occurs through two complementary pathways: psychological readiness and technological engagement. The HBM explains why users are prepared to change, whereas the UEM explains how the application facilitates the implementation of that change in daily life.

The most interesting finding is that Focused Attention and Cue to Action did not show a significant relationship. The non-significant effect of focused attention suggests that physical activity apps do not require users' continuous attention during exercise. Instead, users may need to focus more on physical activity itself, while the app operates passively in the background as a support tool. These findings indicate that focused attention may not be relevant within the scope of mHealth applications for physical activity.

The non-significant effect of cues to action on Healthy Behavior Adoption suggests that external triggers such as reminders, prompts, and notifications may be insufficient to initiate or sustain physical activity when users do not possess strong internal motivation, self-efficacy, or perceived personal relevance. In the HBM, cues to action are often conceptualized as triggers that activate behavior. However, in the context of physical activity applications, such cues may function only as prompts rather than as direct determinants of adoption. Physical activity requires time, effort, planning, and repeated commitment; therefore, reminders alone may not overcome objective barriers such as workload, weather, schedule constraints, or lack of routine. This finding indicates that cues to action may be more effective when they are personalized, timely, and aligned with users' goals and readiness to change, rather than delivered as generic app notifications. The interview findings support this interpretation, as participants reported that reminders or app prompts were less influential than usability, progress feedback, perceived benefits, and confidence in maintaining activity.

In contrast, perceived usability and reward factors aligned more consistently with actual usage experiences. Participants valued Strava for its ease of use and its ability to record activities without complex interactions. Feedback such as distance, duration, and progress logs helped users visualize their achievements. However, digital rewards like badges did not affect all participants equally, suggesting that rewards are more meaningful when linked to personal goals. Fluctuating patterns of Strava usage indicate that behavioral change does not occur linearly. Indeed, a decline in app usage does not necessarily signify failure, as some participants continued their physical activity even after usage dropped. Overall, these findings reinforce the HBM-UEM model by demonstrating that health beliefs initiate change and technology facilitates it, while real-life context determines whether that change is sustained.

VI. Conclusion and Future Work

This study develops and validates an integrated HBM-UEM model to explain behavioral changes among physical activity app users through two primary directions: the psychological and the technological direction. Health belief factors such as perceived benefits, self-efficacy, perceived severity, and objective and subjective barriers influence Healthy Behavior Adoption, whereas usability and reward factors influence Health Technology Engagement. In contrast, cues to action and focused attention did not show a significant influence.

The findings from this study indicate that technology engagement has a stronger impact on behavioral change than the adoption of healthy behaviors. A study on actual Strava usage further reveals that behavioral change is dynamic, influenced by performance feedback, rewards, personal goals, and daily constraints. Overall, the HBM-UEM model offers a more comprehensive explanation by combining users' psychological readiness and user-centric technological support. Future studies should test the model with larger and more diverse groups, including older adults and individuals with chronic conditions. Longer study periods are also needed to examine real behavior changes.

Acknowledgment

This research was supported by grant ZG-2026-007.

References

[1] T. Strain et al., "National, regional, and global trends in insufficient physical activity among adults from 2000 to 2022: a pooled analysis of 507 population-based surveys with 5·7 million participants," Lancet Glob. Health, vol. 12, no. 8, pp. e1232–e1243, Aug. 2024, doi: 10.1016/S2214-109X(24)00150-5.

[2] S. Amagai, S. Pila, A. J. Kaat, C. J. Nowinski, and R. C. Gershon, "Challenges in Participant Engagement and Retention Using Mobile Health Apps: Literature Review," J. Med. Internet Res., vol. 24, no. 4, p. e35120, Apr. 2022, doi: 10.2196/35120.

[3] A. S. Mustafa, N. Ali, J. S. Dhillon, G. Alkawsi, and Y. Baashar, "User Engagement and Abandonment of mHealth: A Cross-Sectional Survey," Healthcare (Switzerland), vol. 10, no. 2, Feb. 2022, doi: 10.3390/healthcare10020221.

[4] M. Mclaughlin et al., "Associations Between Digital Health Intervention Engagement, Physical Activity, and Sedentary Behavior: Systematic Review and Meta-analysis," J. Med. Internet Res., vol. 23, no. 2, p. e23180, Feb. 2021, doi: 10.2196/23180.

[5] M. Milne-Ives, C. LamMEng, C. de Cock, M. H. van Velthoven, and E. M. Ma, "Mobile apps for health behavior change in physical activity, diet, drug and alcohol use, and mental health: Systematic review," JMIR Mhealth Uhealth, vol. 8, no. 3, 2020, doi: 10.2196/17046.

[6] N. K. Janz and M. H. Becker, "The Health Belief Model: A Decade Later," Health Educ. Q., vol. 11, no. 1, pp. 1–47, Mar. 1984, doi: 10.1177/109019818401100101.

[7] Irwin M Rosenstock, "Historical Origins of the Health Belief Model," Health Educ. Monogr., vol. 2, no. 4, pp. 328–335, Dec. 1974, doi: 10.1177/109019817400200403.

[8] H. L. O'Brien and E. G. Toms, "What is user engagement? A conceptual framework for defining user engagement with technology," Journal of the American Society for Information Science and Technology, vol. 59, no. 6, pp. 938–955, Apr. 2008, doi: 10.1002/asi.20801.

[9] H. L. O'Brien, P. Cairns, and M. Hall, "A practical approach to measuring user engagement with the refined user engagement scale (UES) and new UES short form," International Journal of Human Computer Studies, vol. 112, pp. 28–39, Apr. 2018, doi: 10.1016/j.ijhcs.2018.01.004.

[10] L. Degroote, A. De Paepe, I. De Bourdeaudhuij, D. Van Dyck, and G. Crombez, "Effectiveness of the mHealth intervention 'MyDayPlan' to increase physical activity: an aggregated single case approach," International Journal of Behavioral Nutrition and Physical Activity, vol. 18, no. 1, Dec. 2021, doi: 10.1186/s12966-021-01163-2.

[11] G. D. Giebel et al., "Problems and Barriers Related to the Use of Digital Health Applications: Scoping Review," J. Med. Internet Res., vol. 25, p. e43808, May 2023, doi: 10.2196/43808.

[12] S. Bin Jang and M. Kim, "Digital Fitness Revolution: User Perspectives on Fitbit's Role in Health Management," Behavioral Sciences, vol. 15, no. 2, Feb. 2025, doi: 10.3390/bs15020231.

[13] I. Madujibeya, T. Lennie, A. Aroh, M. L. Chung, and D. Moser, "Measures of Engagement With mHealth Interventions in Patients With Heart Failure: Scoping Review," JMIR Mhealth Uhealth, vol. 10, no. 8, p. e35657, Aug. 2022, doi: 10.2196/35657.

[14] C. J. Carpenter, "A Meta-Analysis of the Effectiveness of Health Belief Model Variables in Predicting Behavior," Health Commun., vol. 25, pp. 661–669, 2010, [Online]. Available: https://api.semanticscholar.org/CorpusID:16228578

[15] S. Wu, X. Feng, and X. Sun, "Development and evaluation of the health belief model scale for exercise," Int. J. Nurs. Sci., vol. 7, pp. S23–S30, Sep. 2020, doi: 10.1016/j.ijnss.2020.07.006.

[16] N. S. Alharbi, A. S. AlGhanmi, and M. Fahlevi, "Adoption of Health Mobile Apps during the COVID-19 Lockdown: A Health Belief Model Approach," Int. J. Environ. Res. Public Health, vol. 19, no. 7, p. 4179, Mar. 2022, doi: 10.3390/ijerph19074179.

[17] A. Nasution, A. Yusuf, S. Lean Keng, N. S. Rasudin, Y. P Iskandar, and I. S. Ab Hadi, "Development of Mobile App for Breast Examination Awareness Using Health Belief Model: A Qualitative Study," Asian Pacific Journal of Cancer Prevention, vol. 22, no. 10, pp. 3151–3163, Oct. 2021, doi: 10.31557/APJCP.2021.22.10.3151.

[18] M. Faghih, M. H. Kaveh, M. Nazari, K. Khademi, and J. Hasanzadeh, "Effect of health belief model-based training and social support on the physical activity of overweight middle-aged women: a randomized controlled trial," Front. Public Health, vol. 12, Jan. 2024, doi: 10.3389/fpubh.2024.1250152.

[19] T. Song et al., "Measuring Success of Patients' Continuous Use of Mobile Health Services for Self-management of Chronic Conditions: Model Development and Validation," J. Med. Internet Res., vol. 23, no. 7, p. e26670, Jul. 2021, doi: 10.2196/26670.