Investigating User Perceptions to Mitigate Dropout in Longitudinal Passive Sensing Studies

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Abstract

This paper presents a pilot study exploring user perceptions and engagement in longitudinal passive-sensing systems to provide insights and future directions for dropout prevention research. Leveraging structural equation modeling, we analyzed behavioral intention and use behavior within a mobile sensing app, focusing on privacy and constructs from the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. Privacy, hedonic motivation, and facilitating conditions were identified as significant factors influencing behavioral intention, which, in turn, directly impacted use behavior. These findings highlight the importance of trust-building, user-centered design, and support systems to mitigate dropout and advance passive sensing research.

Keywords

technology adoption, user perceptions, dropout, passive sensing

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1 Introduction

Passive sensing is a method that leverages smartphone sensors and activity logs in a non-intrusive manner and is rapidly emerging as a cornerstone of digital phenotyping. By harnessing the ubiquitous presence of smartphones, passive sensing enables continuous and scalable studies of human behavior in domains such as healthcare, education, and behavioral science [16, 17, 19, 22, 29]. Despite its potential passive sensing technology, it still struggles with high dropout rates in longitudinal studies. Dropout not only threatens the validity and reliability of collected data, but also limits the long-term scalability and effectiveness of passive sensing applications.

Although prior research has extensively examined the causes and consequences of dropout in digital interventions, much of this work has focused on preventing disengagement rather than systematically analyzing the underlying factors that drive users to dropout. Existing approaches such as user feedback mechanisms [15, 26], communication strategies [3, 4], data-driven interventions [5, 7, 12, 20], and personalized engagement techniques [8, 21, 31] focus primarily on mitigating disengagement but often overlook the critical role of user perceptions particularly regarding privacy and performance concerns in shaping dropout decisions. Disengagement driven by trust issues, perceived risks, or lack of transparency remains an unresolved challenge [3, 15, 20] and highlights a gap in understanding how these perceptions influence long-term participation in passive sensing studies.

This paper presents a novel investigation into the role of personal values and user perceptions in mitigating dropout rates by moving beyond conventional engagement models to address the longitudinal challenges of attrition in passive sensing systems. We extend the Unified Theory of Acceptance and Use of Technology (UTAUT2) by integrating privacy as a central construct and adopting a longitudinal perspective on technology adoption from initialization to sustained use, while examining how privacy concerns and trust influence dropout over time. The paper details the conceptual model, presents preliminary findings from a pilot study and outlines implications for designing user-centric sustainable passive sensing systems. Through this work, our aim is to advance the reliability and scalability of passive sensing for digital phenotyping and other applications.

2 Related Work

Mitigating dropout is essential to maintain data quality, ensure research validity, and preserve the representativeness of longitudinal studies. High dropout rates distort findings, introduce bias, and reduce the reliability of behavioral models, particularly in passive

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sensing research. To address this challenge, Chien et al. [7] emphasized customized interventions to address user needs in Internet-based cognitive behavioral therapy while Park et al. [21] identified poor timing and repetitive interventions as key drivers of disengagement in Just-In-Time systems. Jakob et al. [12] applied churn prediction models to detect and prevent dropout in digital health programs. Birk et al. [3] highlighted personalization through avatar customization to reduce attrition in self-improvement apps. Pan et al. [20] underscored the detrimental impact of dropout on data quality in learning studies and stressed the need for robust mitigation strategies. Although these studies recognize dropout as a critical issue, they focus primarily on surface-level engagement interventions rather than addressing its underlying contextual drivers and highlight the need for more research, particularly in passive sensing environments.

User perceptions including personal values and behavioral drivers are crucial in shaping trust, satisfaction, and engagement with systems. Studies indicate that aligning system design with users' personal goals and ensuring transparency in data usage significantly decrease dropout risk [10, 14]. Personal values drive behavior as individuals align their actions with priorities [24] while fostering a sense of being heard enhances empathy and engagement [23]. Privacy and trust are especially critical in sensitive domains like healthcare where they significantly influence technology adoption [9]. The Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended version UTAUT2 offer robust frameworks for understanding user perceptions and adoption behaviors, integrating constructs such as hedonic motivation, habit, and price value. In healthcare UTAUT2 highlights the critical role of privacy and trust in telemedicine adoption [9] while Tsai et al. [27] identified technology anxiety as a barrier to wearable health technology use. Similarly, UTAUT2 has been applied in education to assess the sustainability of federated and mobile learning systems with a focus on trust and usability [1, 11]. However, despite its broad applicability UTAUT2 has primarily been used to assess initial adoption and usability rather than long-term participation and dropout. Shachak et al. [25] have critiqued this approach calling for more multidimensional models that address complex factors in longitudinal studies.

Among these factors, privacy emerged as a pivotal element that influences user retention. Studies have shown that concerns related to data misuse, lack of transparency, and limited user control contribute significantly to participant attrition [2, 9, 18]. Dhagarra et al. [9] identified privacy and trust as key determinants of technology acceptance, while Han et al. [11] emphasized the need to balance privacy with usability to enhance system efficiency. Baig et al. [2] highlighted the importance of user-friendly privacy measures, and McCoy et al. [18] underscored the role of transparency in building trust and reducing disengagement. Despite these insights, few studies have examined how privacy concerns shape behavioral intentions over time and contribute to dropout in passive sensing systems.

Privacy has been widely recognized as a critical factor influencing user dropout, yet its role in long-term disengagement remains largely unexplored in theoretical frameworks such as UTAUT2. Previous studies using UTAUT2 have focused mainly on technology adoption and usability at a single point in time, rather than examining how user perceptions evolve throughout a study [1, 13, 27, 30]. Although these studies have examined key factors such as effort expectancy, social influence, and hedonic motivation, they have not explicitly investigated how these perceptions change over time and influence sustained participation. In contrast, our study extends UTAUT2 by integrating privacy as a central construct and tracking user perceptions longitudinally to assess their role in long-term dropout trends. By systematically capturing these insights over time in a manner that minimizes survey fatigue and preserves data integrity, we aim not only to understand why users disengage but also to implement strategies that proactively reduce the likelihood of dropout in passive sensing studies.

By integrating privacy into UTAUT2 and tracking perceptions longitudinally, this study introduces a novel framework to understand and mitigate dropout in passive sensing research. Our findings provide actionable insights on designing privacy-based engagement strategies that enhance long-term participation while preserving data integrity.

3 Framework Development

Building on the UTAUT2 framework, this study incorporates privacy as a critical construct to address concerns specific to passive data collection systems. Some constructs of UTAUT2, such as performance expectancy and price value were excluded from this study due to their limited applicability within the context of a passive data collection application. Performance expectancy, which assesses the perceived benefits of a technology in enhancing user tasks, was deemed less relevant because the app's primary function is passive data collection without directly influencing or improving user tasks. Similarly, price value, which evaluates the trade-off between an app's benefits and its monetary cost, was considered inapplicable given that the app is entirely free to download and use, with no associated financial implications for participants. By focusing on constructs that are contextually aligned with passive sensing applications, we develop a framework that offers meaningful insights into user behavior and engagement.

3.1 Effort Expectancy

Effort expectancy measures the degree of ease associated with the use of a system [28]. It underscores the importance of simplicity in installation, configuration, and functionality with minimal disruptions. These factors are crucial for delivering a seamless, non-intrusive user experience that fosters retention.

Hypothesis H1: Effort expectancy has a significant positive effect on behavioral intention.

3.2 Social Influence

Social influence reflects the degree to which individuals perceive that others, such as family or friends, expect them to use the system [28, 30]. Peer recommendations and shared values further encourage adoption, reinforcing the willingness of users to participate.

Hypothesis H2: Social influence has a significant positive effect on behavioral intention.

3.3 Hedonic Motivation

Hedonic motivation refers to the enjoyment or satisfaction derived from using a system [28]. Fostering a positive emotional connection, even for systems operating in the background, can enhance long-term retention.

Hypothesis H3: Hedonic motivation has a significant positive effect on behavioral intention.

3.4 Facilitating Conditions

Facilitating conditions encompass the resources and support available to ensure seamless use of the app [28]. Reliable infrastructure and technical support further boost user confidence and sustain engagement.

Hypothesis H4a: Facilitating conditions have a significant positive effect on behavioral intention.

Hypothesis H4b: Facilitating conditions have a significant positive effect on use behavior.

3.5 Habit

Habit refers to the extent to which users perform behaviors automatically based on learning [30]. Consistent data collection depends on the integration of habitual actions into user routines. By making these actions easy to adopt, the system can ensure a seamless experience and sustained engagement.

Hypothesis H5a: Habit has a significant positive effect on behavioral intention.

Hypothesis H5b: Habit has a significant positive effect on use behavior.

3.6 Privacy

Privacy represents user perceptions of how securely and transparently their data are collected, stored, and used. Addressing privacy concerns, such as data misuse and lack of transparency, is crucial to foster trust, with clear communication and robust safeguards playing a key role in driving behavioral intention and sustained engagement. [9, 16].

Hypothesis H6a: Privacy has a significant effect on behavioral intention.

Hypothesis H6b: Privacy has a significant effect on use behavior.

3.7 Behavioral Intention

Behavioral intention measures the willingness of users to engage with a system and serves as a direct predictor of use behavior. Strengthening behavioral intention through the aforementioned constructs can significantly impact user engagement and long-term participation [28].

Hypothesis H7: Behavioral intention has a significant positive effect on use behavior.

By integrating privacy into the UTAUT2 framework, this study addresses critical research gaps in passive sensing and provides actionable insights for designing systems that balance usability, trust and privacy.

4 Case Study: EV User Study for the BMS Algorithm

A case study of the proposed framework was conducted on a Delayed-Full Charging (DFC) Battery Management System (BMS) algorithm designed to mitigate battery degradation in electric vehicles (EVs) by delaying full charging. The algorithm leverages behavioral insights derived from mobile life-logging data to reduce prolonged exposure to high state-of-charge (SOC) levels, thereby extending battery lifetime.

4.1 Setup and Data Collection

This study enrolled 44 participants, each with an Android smartphone and an EV, to evaluate perceptions on the EV Analyzer (EVApp). EVApp is a mobile application designed to passively collect data on user behavior, focusing on driving patterns and phone usage behaviors. The application collects, processes, and stores a wide range of sensor and usage data, including bluetooth connections, GPS locations, phone calls, app visibility states, device unlock events, step detection, ambient light levels, and activity recognition. By automating these processes and operating unobtrusively in the background, the application provides comprehensive information to optimize the BMS algorithm while ensuring minimal user intervention.

To manage feasibility and ensure data quality, participant recruitment was conducted in batches. This study specifically analyzed data from Batch 2 (44 participants), incorporating refinements based on observations from an earlier participant group, Batch 1 (67 participants), which had experienced high dropout rates. Recruitment was carried out through weekly ads on EV community blogs, where eligible participants, EV owners using Android devices, could voluntarily sign up.

The batch approach was necessary to maintain a manageable number of participants for customer support and facilitate iterative improvements to the features of EVApp. A key distinction in Batch 2 was the introduction of structured survey assessments, aimed at systematically evaluating user perceptions and improving retention. Unlike Batch 1, which lacked formal engagement mechanisms, this study integrates participant feedback to analyze how privacy concerns, trust, and engagement strategies influence sustained participation in passive sensing systems.

4.2 Demographics

The participant group was composed entirely of males (100%), with the following age distribution: 7% were 20-29 years old, 30% were 30-39 years old, 46% were 40-49 years old and 17% were 50-59 years old. In terms of educational background, 10% of the participants had a high school diploma or lower, 60% had a bachelor's degree, and 30% had achieved a master's degree. These demographic details provide context for interpreting the responses to the survey and the engagement patterns observed in the study.

4.3 Survey Design

The TAM survey assessed UTAUT2 constructs in the context of EVApp data collection, with a focus on effort expectancy and privacy due to their critical role in shaping user perceptions and app adoption. Effort expectancy measured ease of use, emphasizing

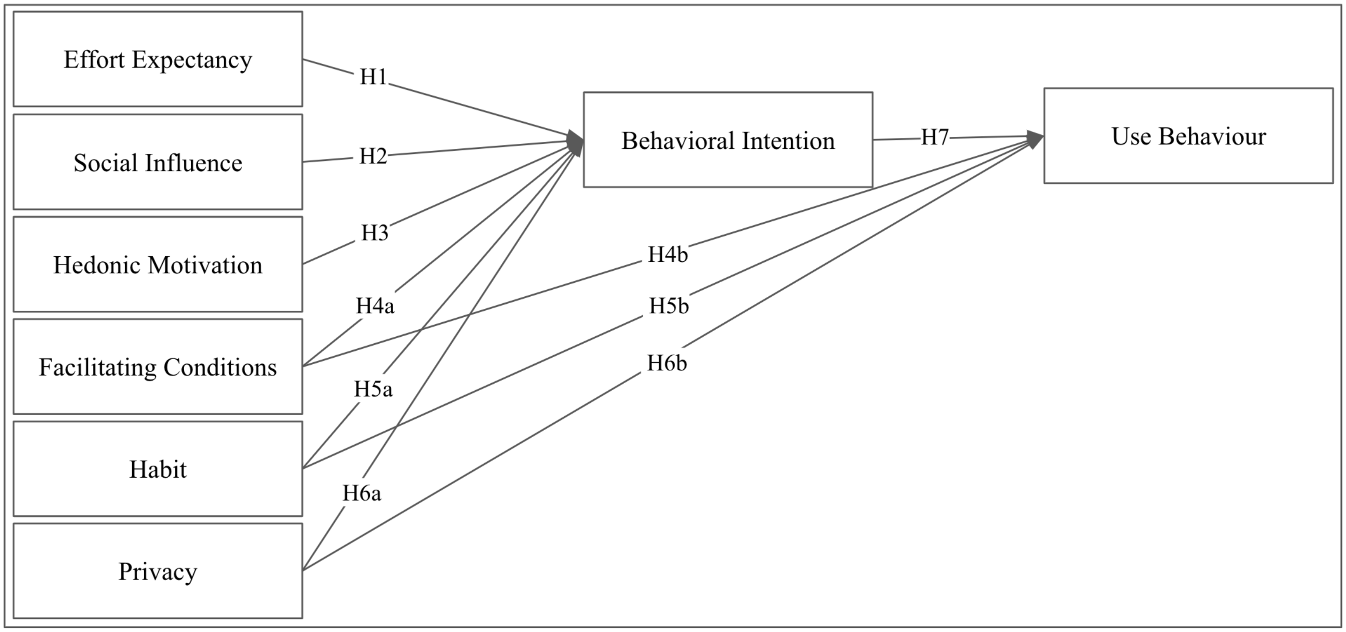

Figure 1: Proposed Framework

seamless functionality with minimal user input, while privacy evaluated user confidence in secure, transparent, and ethical data handling. To balance completeness and survey fatigue, social influence and hedonic motivation were measured with single-item questions, leveraging evidence that single-item measures can be effective under practical constraints [6].

The two-phase survey captured initial perceptions (e.g., trust and recommendation intent) in Week 0 and user experiences (e.g., ease of setup and motivation) in Week 2, using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Conducted in Korean, the survey was designed for clarity and accessibility. Regression analysis confirmed the predictive power of the method to understand user engagement and adoption dynamics. Feedback from the first batch(batch 1) of participants and the literature review informed revisions for subsequent batches, addressed dropout factors, and refined the survey to better capture engagement challenges. The pilot testing further improved clarity, reduced bias, and streamlined the structure, setting a strong foundation for its refinement at week 8.

The table below (Table 1) provides an overview of the questions, the week they were administered, and their associated UTAUT2 constructs.

4.4 Preliminary Results

All constructs in the model were first validated using face validity and regression analysis, providing an initial evaluation of user perceptions. The regression analysis revealed that the model explained 52.5% of the variance in behavioral intention ($R^2 = 0.525$) and 43.8% in use behavior ($R^2 = 0.438$), highlighting the predictive strength of the constructs. As all participants were compliant and answered all the survey questions, data cleaning and pre-processing were unnecessary. Subsequently, partial least squares structural equation modeling (PLS-SEM) was performed in Python, selected for its suitability to analyze complex models with latent variables and small sample sizes, making it ideal for this pilot study. This approach provided a foundational understanding of the relationships between constructs, offering insights into user attitudes and behaviors in the context of the EVApp.

Behavioral intention strongly influenced use behavior, with privacy, hedonic motivation, and facilitating conditions emerging as significant predictors. Social influence and habit also shaped behavioral intention, emphasizing the roles of peer influence and routine behaviors. However, privacy, habit, and facilitation conditions did not show direct effects on use behavior, suggesting that their impact is mediated by behavioral intention. These findings underscore the importance of addressing privacy concerns, improving user satisfaction, and providing support systems to strengthen behavioral intention and prevent dropout in passive data collection systems.

Table 2 presents the preliminary results of the hypothesis testing, detailing the path coefficients, t-values, and significance levels. The results illustrate the varying degrees of influence that each construct exerts on behavioral intention (BI) and use behavior (UB).

Figure 2 presents a visual representation of the preliminary model, illustrating the relationships between the constructs and highlighting statistically significant pathways. This figure offers a concise overview of the framework's structure and the relative influence of each construct.

5 Discussion

5.1 Implications

The results highlight the importance of privacy, hedonic motivation, and facilitating conditions in shaping behavioral intention,

Table 1: Survey Questions with Constructs

Week	Questions (English)	Construct (English)
Week 0	I believe the people around me would use EVApp if I referred it.	Social Influence
Week 0	I trust EVApp to protect my data throughout the study.	Privacy
Week 2	I find it easy to understand how the EVApp works.	Effort Expectancy
Week 2	Setting up data collection in EVApp was effortless.	Effort Expectancy
Week 2	It's engaging to see the progress of data collection.	Hedonic Motivation
Week 2	Technical support for EVApp is easily available if needed.	Facilitating Conditions
Week 2	Connecting to Bluetooth and charging while driving is easy to adopt to my routine.	Habit
Week 2	I believe the app uses secure methods to handle my data during transfer.	Privacy
Week 2	I am comfortable with how the app collects the data.	Privacy
Week 2	I am motivated to ensure the EVApp remains active on my device during the study.	Behavioral Intention
Week 2	I regularly monitor the EVApp's data progression, Kakao Channel updates, and Announcement Board.	Use Behavior

Table 2: Preliminary Results

Hypothesis	Path Coefficient (β)	t-Value	p-Value	Supported?
H1: Effort Expectancy → BI	0.134	1.950	0.051	Partial
H2: Social Influence → BI	0.112	2.020	0.044	Yes
H3: Hedonic Motivation → BI	0.188	3.220	<0.001	Yes
H4a: Facilitating Conditions → BI	0.180	3.120	0.001	Yes
H4b: Facilitating Conditions → UB	0.050	1.200	0.339	No
H5a: Habit → BI	0.113	2.240	0.026	Yes
H5b: Habit → UB	0.050	0.960	0.339	No
H6a: Privacy → UB	0.167	0.970	0.332	No
H6b: Privacy → BI	0.316	3.130	0.002	Yes
H7: Behavioral Intention → UB	0.360	4.200	<0.001	Yes

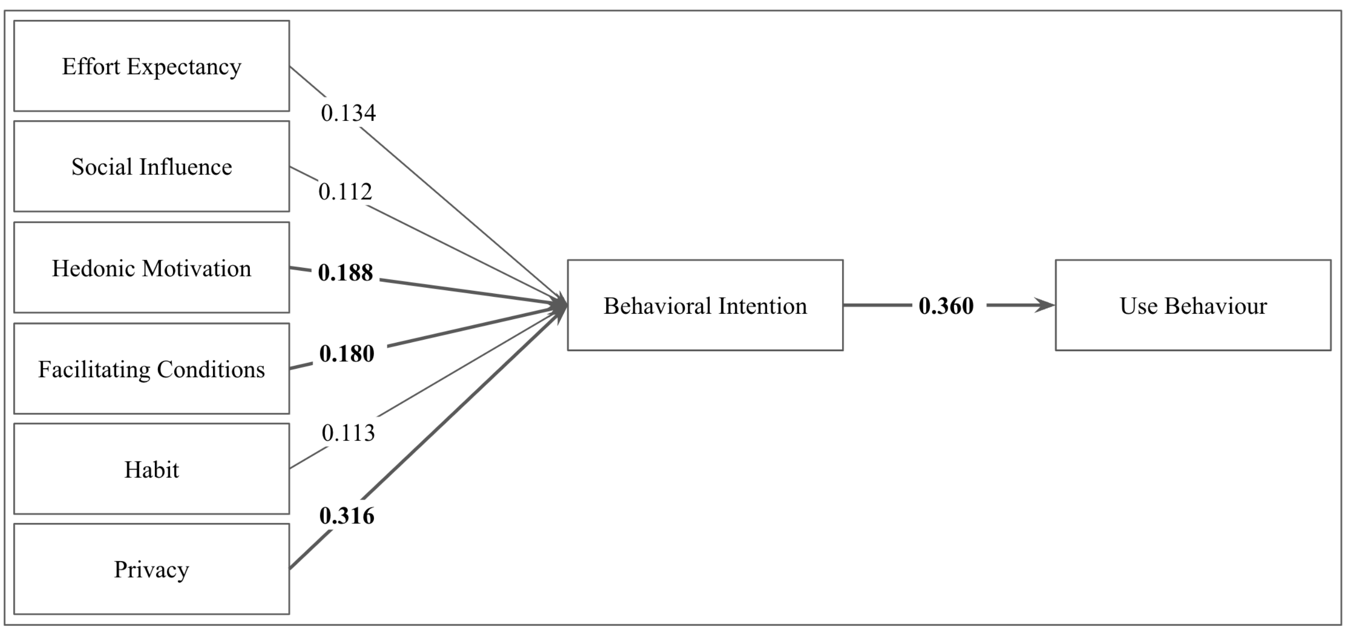

Figure 2: Preliminary Model of Constructs and Their Relationships

which directly influences use behavior. Privacy emerges as the most critical factor, highlighting the need for trust-building measures such as transparency and privacy updates on the app. Hedonic motivation and facilitating conditions play key supporting roles, suggesting that improving user enjoyment through gamification, progress updates, and enhanced support infrastructure could be beneficial. Although effort expectancy, social influence, and habit had weaker but still significant impacts on behavioral intention, these findings highlight the importance of maintaining ease of use, fostering positive impressions within social circles, and encouraging habitual usage routines.

Early observations suggest that enhanced privacy assurances and engagement strategies may contribute to improved user retention, as reflected in more positive feedback and increased user interest in Batch 2. Dropout rates have decreased significantly, from 23.9% in Batch 1 (16 out of 67 participants) to 9.1% in Batch 2 (4 out of 44 participants), indicating that improvements in engagement strategies, better communication, and increased participant trust may foster higher retention levels. Furthermore, the increase in participant appreciation and positive feedback suggests that the study has helped improve user knowledge and interest in the app, further contributing to sustained participation. Although these dropout rates are provided as preliminary references, a more comprehensive comparison of engagement metrics, including app usage patterns and retention trends, will be conducted at the conclusion of the study. Although a formal longitudinal analysis of dropout trends is planned for future research, these preliminary findings provide valuable insights on how strategic modifications in privacy assurance and user engagement can improve long-term retention. In the following weeks of the study, efforts will prioritize privacy assurance, engaging features, and reliable support, while monitoring behavioral intention and use behavior to assess the impact of these interventions and guide future improvements.

5.2 Limitations

The findings of this pilot study should be interpreted with certain limitations, which will be addressed in the final study. One key limitation is the availability of longitudinal data. The results presented in this study are based on responses collected at week 2, as the study has not yet reached its full duration of eight weeks. Consequently, the findings do not yet capture how user perceptions, privacy concerns, and engagement levels evolve over time. Furthermore, while preliminary dropout rates have been included for reference, a complete comparison of engagement metrics, including system usage data and retention trends, will be conducted at the conclusion of the study to provide a more comprehensive analysis of user participation. Future analyses will leverage the complete dataset to assess longitudinal trends and further refine dropout mitigation strategies.

To mitigate survey fatigue, constructs such as social influence and hedonic motivation were assessed using single-item measures in this phase. However, the final study will incorporate multi-item measures for all constructs, enabling more comprehensive and rigorous analyses. In addition, this pilot study serves as a basis for evaluating the test-retest validation, which will further strengthen the reliability of the findings in subsequent research. This iterative design ensures that the final survey provides a deeper and more nuanced understanding of user engagement trends and perceptions, significantly improving the overall validity and practical applicability of the study.

6 Conclusion

This pilot study offered foundational insights into user engagement and retention within passive data collection applications, utilizing the UTAUT2 framework with privacy as a central construct. Key relationships were identified with privacy, hedonic motivation, and facilitating conditions significantly influencing behavior intention and, subsequently, use behavior. The phased survey captured initial trust and engagement intentions along with user experiences, providing a preliminary understanding of the factors that shape sustained participation. To address the limitations of this pilot phase, such as the use of single-item measures for some constructs, the final study will incorporate multi-item measures for all constructs, enabling more robust and comprehensive analyses. Additionally, the final study will evaluate test-retest validation, ensuring reliability and offering a deeper exploration of user engagement dynamics. This iterative approach aims to deliver actionable insights for designing privacy-preserving, user-centric, and scalable passive sensing systems.

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