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Research Article

A PREDICTION-ORIENTED ACCEPTANCE SCORE FOR SUSTAINED mHEALTH USE: INTEGRATING HOT – FIT AND TAM IN COMMUNITY-BASED DENGUE SURVEILLANCE

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Abstract
Sustaining the use of mobile health (mHealth) applications is an important challenge in community-based dengue surveillance. However, the combined roles of human capabilities, technology quality, and organizational support in shaping continued use require further examination in this setting. This study evaluated mHealth acceptance among dengue larvae monitoring cadres by integrating the Human-Organization-Technology Fit (HOT-Fit) framework and the Technology Acceptance Model (TAM), and explored a preliminary Acceptance Score (AS) for prediction-oriented decision support. A cross-sectional study involving 60 dengue larvae monitoring cadres used a questionnaire comprising 18 indicators across six constructs. We analyzed the hypothesized relationships using partial least squares structural equation modeling (PLS-SEM) in SmartPLS4. Predictive performance was assessed using PLSpredict. The Pearson correlation and regression analyses were used to examine the relationship between the proposed AS and continuance intention using SPSS 25. Human literacy ($\beta = 0.32$), technology quality ($\beta = 0.35$), and organizational support ($\beta = 0.44$) were positively associated with perceived usefulness. Perceived usefulness was positively associated with user satisfaction ($\beta = 0.62$) and continuance intention ($\beta = 0.57$); all reported paths were statistically significant ($p < 0.001$). The model explained 62% of the variance in perceived usefulness, 58% in user satisfaction, and 52% in continuance intention. The AS was positively correlated with continuance intention ($r = 0.488$, $p < 0.001$). Integrating HOT-Fit and TAM offers a framework for examining continued mHealth use in community-based dengue surveillance. The preliminary AS may inform future implementation support, but independent validation is required before operational use.

Keywords: Decision Support, Digital Health Evaluation, Dengue Surveillance, HOT-Fit, PLS-SEM, Technology Acceptance Model.

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INTRODUCTION

Dengue fever remains one of the most significant vector-borne diseases affecting tropical and subtropical countries worldwide (Zeng et al., 2021). The increasing incidence of dengue fever has become a major public health concern, particularly in low- and middle-income countries where environmental conditions, population density, and urbanization facilitate mosquito breeding and disease transmission (Samal et al., 2020; Nashwan et al., 2023). Dengue fever continues to place a significant burden on healthcare systems, communities, and national disease control programs, particularly in Southeast Asian countries, including Indonesia (Tsheten et al., 2021; Zeng et al., 2021). Community-based vector surveillance remains a crucial strategy for dengue prevention and control (Sulistyawati et al., 2023). In Indonesia, dengue larvae monitoring cadres, commonly known as *jumantik* cadres, play a crucial role in conducting household inspections, monitoring mosquito breeding sites, reporting larvae findings, and supporting community-level public health education. These cadres serve as the frontline workforce in dengue surveillance activities, particularly in primary health care and community-based prevention programs (Ridha et al., 2023; Sulistyawati et al., 2023).

In recent years, the implementation of mobile health (mHealth) technology has grown rapidly within public health systems (Mccool et al., 2021). mHealth apps are increasingly being used to enhance disease surveillance, data reporting, monitoring efficiency, and communication between cadres and healthcare institutions. Previous studies have shown that mHealth interventions can improve reporting timelines, data accuracy, and operational efficiency in infectious disease surveillance programs (Wang et al., 2022). The effective deployment of mHealth technologies in community-based settings remains challenging, despite their potential advantages. Several barriers have been reported, including limited digital literacy, unstable internet connectivity, inadequate technical support, insufficient training, and low user engagement among cadres. These barriers can reduce user satisfaction and limit the long-term sustainability of digital health interventions (Kaboré et al., 2022; Nie et al., 2023). Existing studies on mHealth adoption have primarily focused on healthcare professionals, hospital-based systems, telemedicine users, or patient-centered applications (Willis et al., 2022; Wosny et al., 2023).

Although the adoption of mHealth has been studied in various healthcare settings, evidence remains limited regarding how individual capabilities, technology quality, and organizational support jointly relate to perceived usefulness and continued use among community-based dengue surveillance cadres. This context warrants specific attention because cadres perform surveillance tasks outside conventional clinical settings and may face different combinations of digital literacy, technical, and organizational challenges. The Human-Organization-Technology Fit (HOT Fit) framework provides a basis for examining human, technological, and organizational conditions, while the Technology Acceptance Model (TAM) helps explain perceived usefulness and technology-related responses. Recent studies have highlighted the importance of system quality, organizational support, perceived usefulness, and user satisfaction in forming continuance intention toward mHealth utilization. (Tao et al., 2023). The HOT-Fit framework provides a basis for examining the relationships among human, technological, and organizational dimensions, whereas TAM-related constructs help explain users' perceptions of usefulness and their responses to technology. Integrating these perspectives enables the present study to examine these dimensions within a single proposed framework.

A further practical challenge is translating explanatory findings into information that can support implementation planning. However, a weighted Acceptance Score (AS) derived from structural model results should be regarded as preliminary until its performance is independently validated. Accordingly, this study had two objectives: (1) to examine the hypothesized relationships of human literacy, technology quality, and organizational support with perceived usefulness, and of perceived usefulness and user satisfaction with subsequent continuance intention; and (2) to develop an exploratory AS based on the estimated structural relationships and examine its association with continuance intention. By addressing these objectives, a prediction-oriented approach is used while identifying the further validation required before practical implementation.

RESEARCH METHOD

The factors impacting dengue larvae monitoring cadres' adoption of mHealth apps were examined using a cross-sectional design. This study utilized a simple integration of the HOT-Fit framework (Ahmetoglu & Cob, 2022; Zhai et al., 2022; Sparidaens et al., 2023) and the TAM (Al-Qaysi et al., 2021; Bastan et al., 2021) to assess the determinants of user satisfaction, perceived usefulness, and

continuance intention using mHealth apps. This study adopts a prediction-oriented approach using PLS-SEM, which is suitable for exploratory studies, small sample sizes, and complex latent variable analysis (J. Hair et al., 2022; Sarstedt et al., 2022; Kante & Michel, 2023; Shela et al., 2023).

This study was conducted at a community health center in Bungur, Senen, and Kemayoran, Jakarta, Indonesia, from February 10 to May 30, 2023. 60 dengue larvae monitoring cadres participated in this study in a community-based dengue fever surveillance program. The sample size was determined in accordance with PLS-SEM guidelines (Kock, 2018; Petter & Hadavi, 2023) and a rule of thumb (Lakens, 2022; Althubaiti, 2023) which establishes a minimum sample size of 10 times the total number of the 6 constructs being analyzed. These cadres are community health volunteers responsible for monitoring mosquito breeding sites, conducting larvae inspections, recording surveillance findings, and supporting household-level dengue prevention activities. Purposive sampling was used to choose respondents based on pre-established inclusion criteria. The criteria used for inclusion were: active dengue larvae monitoring cadres, experience using mHealth apps, and willingness to participate voluntarily in the study.

The study instrument was developed based on previous validation studies related to the HOT-Fit (Ahmetoglu & Cob, 2022; Zhai et al., 2022; Sparidaens et al., 2023) and TAM frameworks (Al-Qaysi et al., 2021; Bastan et al., 2021). The questionnaire consisted of 18 indicators spread across 6 latent constructs, and the grid instrument for mHealth acceptance is shown in Table 1.

Table 1. Instrument Grids for mHealth Acceptance

Construct	Operational Definition	Indicator Coverage	Number of Items
Human Literacy (HL)	Ability and independence in operating the application	Digital ability and independent operation	3
Technology Quality (TQ)	Perceived usability, system stability, and responsiveness	Usability, stability, and responsiveness	3
Organizational Support (OS)	Institutional support, training adequacy, and technical assistance	Organizational support, training, and assistance	3
Perceived Usefulness (PU)	Perceived usefulness of the application for surveillance tasks	Usefulness for task performance	3
User Satisfaction (US)	Overall satisfaction with application use	Overall user satisfaction	3
Continuance Intention (CI)	Intention to continue using the application in future activities	Intention for continued use	3

In Table 1, Human literacy (HL) assessed the user's ability and independence in operating an application. Technology quality (TQ) was assessed through respondents' perceptions of the application's usability, system stability, and responsiveness (Bastan et al., 2021; Ahmetoglu & Cob, 2022; Zhai et al., 2022). Organizational support (QS) assessed institutional support, adequacy of training, and availability of technical assistance (Ahmetoglu & Cob, 2022; Zhai et al., 2022). Perceived usefulness (PU) measured respondents' perceptions of the application's usefulness in supporting surveillance tasks (Al-Qaysi et al., 2021; Bastan et al., 2021). User satisfaction (US) assessed overall satisfaction with the application's use (Bastan et al., 2021; Sparidaens et al., 2023)While continuance intention measured respondents' continuance intention to use the application in future activities (Al-Qaysi et al., 2021; Bastan et al., 2021) A five-point Likert scale, which goes from 1 (strongly disagree) to 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree), was used to measure each item. For community-based dengue surveillance settings, the questionnaire was examined and contextually modified. The exact wording of the statement items, along with their respective sources, is provided in the supplementary instrument.

This study applies a simple integration of the HOT-Fit and TAM. The HOT-Fit framework is used to represent the human, technology, and organizational dimensions through technology quality and organizational support. Meanwhile, the TAM constructs are used to evaluate the behavioral acceptance dimensions through perceived usefulness, user satisfaction, and continuance intention. As shown in Figure 1, the conceptual model hypothesizes that:

H1: Human literacy positively influences perceived usefulness

H2: Technology quality positively influences perceived usefulness
H3: Organizational support positively influences perceived usefulness
H4: Perceived usefulness positively influences user satisfaction
H5: User satisfaction positively influences continuance intention

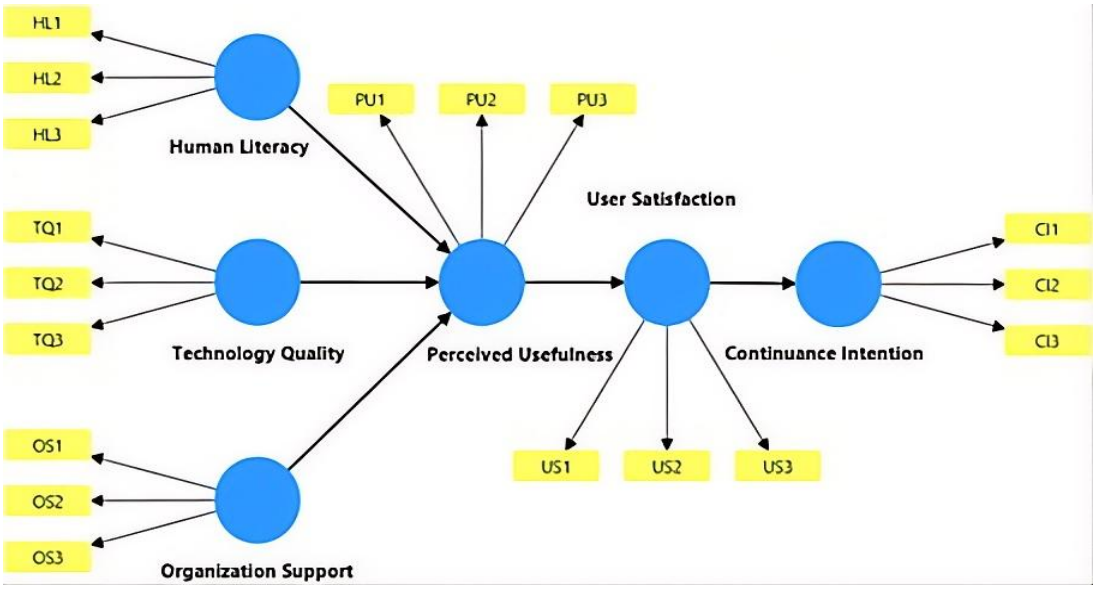

Figure 1. Conceptual Framework

PLS-SEM with SmartPLS 4 and SPSS 25 software was used to analyze the data. Figure 2 illustrates the three stages of the analysis: 1. Assessment of measurement models, 2. Assessment of structural models, 3. Acceptance score development. Measurement model evaluation was conducted to assess convergent validity, discriminant validity, internal consistency reliability, and indicator reliability (J. Hair et al., 2022; Shela et al., 2023). Outer loading values were used to assess the indicator's reliability, with a recommended threshold of greater than 0.70. Cronbach's alpha and Composite Reliability (CR) were used to measure internal consistency reliability; values above 0.70 were considered acceptable. The Average Variance Extracted (AVE) was used to assess convergent validity; a value greater than 0.50 indicates sufficient convergent validity. The Heterotrait-Monotrait Ratio (HTMT), with a suggested cutoff below 0.90, was used to evaluate discriminant validity.

The structural model evaluation included bootstrapping procedures, t-statistics, analysis of a path coefficient, coefficient of determination (R^2), size of the effect (f^2), p-values, predictive relevance (Q^2predict), and model fit indices (Kante & Michel, 2023; Sarstedt et al., 2022). PLS prediction analysis was conducted following the systematic procedure recommended by Sarstedt et al. (2022). 5,000 bootstrap resamples were used to evaluate the statistical significance of hypothesized relationships. Hypotheses were considered significant at $p < 0.05$. The coefficient of determination (R^2) was interpreted as: 0.25 = weak, 0.50 = moderate, and 0.75 = substantial exploratory power. Effect size (f^2) values were interpreted as: 0.02 = small, 0.15 = medium, 0.35 = large effect. Predictive relevance was evaluated by Q^2predict values, where positive Q^2predict values indicated the model's predictive relevance (J. Hair et al., 2022; Sarstedt et al., 2022; Kante & Michel, 2023). To evaluate the out-of-sample predictive relevance of the theoretical model, a PLS prediction analysis was conducted following the systematic procedure recommended by Sarstedt et al. (2022). In line with modern PLS-SEM guidelines, the evaluation of predictive power went beyond the in-sample explanatory power (R^2) to ensure the model's generalizability to new observations and demonstrate that the structural model possesses out-of-sample predictive capability. This assessment used a 10-fold cross-validation configuration with 10 replications. The Root Mean Squared Error (RMSE) values from the PLS model and the baseline Linear Model (LM) were compared to perform a thorough item-level evaluation. According to the decision rule, the PLS model has a high degree of predictive power if all indicator items have reduced RMSE values when compared to the baseline LM model (Sarstedt et al., 2022).

An acceptance score (AS) was developed to measure the likelihood of mHealth adoption among dengue larvae monitoring cadres and can function as an empirically derived adoption index. This score was constructed using significant predictors identified through PLS-SEM analysis. Each construct was

weighted based on its standardized path coefficient, thereby reflecting its relative contribution to technology acceptance and the continuance intention of using it. A higher score indicates a greater likelihood of mHealth adoption and continuance intention of using it. The acceptance score is calculated as follows: equation (1).

$$AS = \sum \beta_i X_i \qquad (1)$$

After the AS values were calculated, empirical validity was conducted using SPSS software to extend the practical applicability of the AS, assessing convergent validity (Pearson correlation) by correlating AS with CI and the predictive ability of the AS by linear regressing CI against AS (R^2, β, p-value), enabling its use for decision support regarding individual assessment, targeted interventions, and monitoring and evaluation. The resulting regression equation enabled the derivation of an integrated prediction equation by substituting the AS formula into the regression model (equation 2).

$$CI = a + b\,(AS) \qquad (2)$$

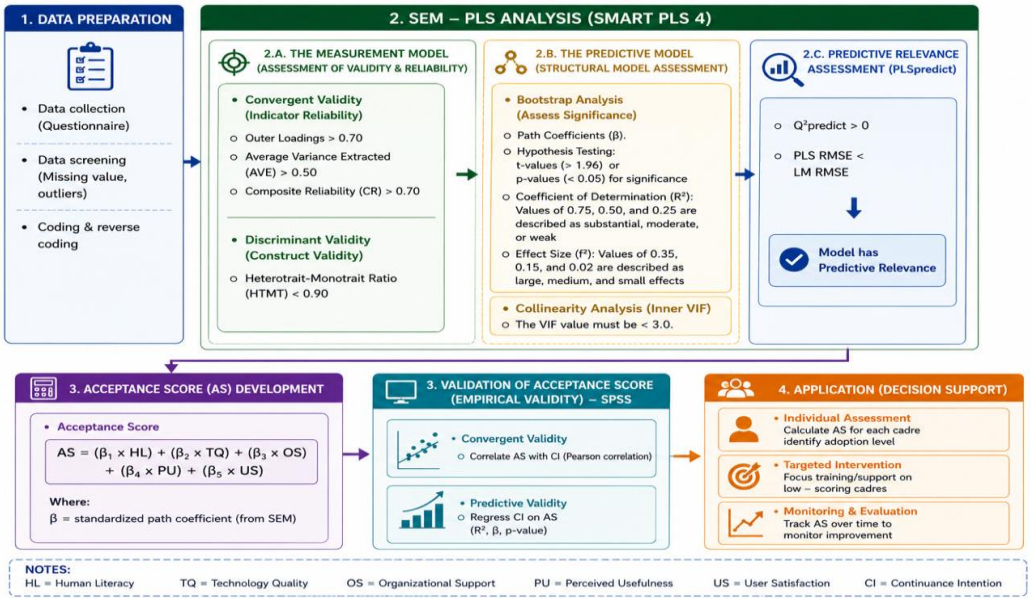

Figure 2. Research design

The study's methods were carried out in compliance with community-based public health studies and ethical guidelines for research involving human subjects. The Ethical Committee of Medicine at Universitas Indonesia approved this study with the ethical approval number KET–509/UN2·F1/ETIK/PPM. 00.02/2022.

RESULTS AND DISCUSSION

Respondent Characteristics

60 dengue larvae monitoring cadres participated in this study. As shown in Table 2, all respondents were female, reflecting the dominant involvement of women in community-based dengue surveillance activities. 51.7% of respondents were between the ages of 30 and 45, followed by those over 45 (25.0%) and under 30 (23.3%). Regarding educational background, the majority of cadres had completed high school (61.7%), while 25.0% had a junior high school degree, and 13.3% had a college degree. Regarding work experience, half of the respondents (50.0%) had been in cadres for one to five years, suggesting a significant amount of experience in public health surveillance activities.

Table 2. Characteristic Respondent

Characteristic	Category	n	%
Age	< 30 years	14	23.3
	30 – 45 years	31	51.7
	> 45 years	15	25
Education	Junior High School	15	25
	Senior High School	37	61.7
	College	8	13.3
Time as a cadre	< 1 year	13	21.7
	1 – 5 years	30	50
	> 5 years	17	28.3

In Table 2, the demographic profile of the respondents indicates that dengue larvae monitoring cadres are generally middle-aged adults with a secondary education background and one to five years of field experience. This profile reflects a cadre that possesses adequate practical experience while also being capable of adapting to digital innovations. Current evidence suggests that cadres are more likely to adopt mHealth technologies rather than simply relying on higher levels of formal education if they possess sufficient operational experience, receive sustained organizational support, and use applications that are simple and relevant to their daily tasks (Addotey-Delove et al., 2023; Kachimanga et al., 2024). Similarly, the effectiveness of implementation studies on the digitalization of health among cadres depends on the alignment between user capabilities, technology usability, and organizational readiness, all of which are crucial elements for successful technology adoption. (Blondino et al., 2024). Therefore, the respondent characteristics observed in this study provide an appropriate context for evaluating the integrated HOT-Fit and TAM model, as the participants represent the implementation of mHealth apps for dengue larvae surveillance.

Measurement Model Assessment

The measurement model was assessed using discriminant validity, convergent validity, indicator reliability, and internal consistency reliability. The assessment was conducted following the recommended guidelines for PLS-SEM. All indicators demonstrated satisfactory results, as shown in Table 3; the required threshold of 0.70 is exceeded by the external loadings, which range from 0.75 to 0.93, and each indicator reflects the latent constructs associated with it. Internal consistency results also showed acceptable values. Composite reliability scores varied from 0.72 to 0.99, and Cronbach's alpha values ranged from 0.70 to 0.85.

Table 3. Measurement Model Results

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
HL	HL1	0.80	074	0.75	0.66
	HL2	0.80			
	HL3	0.83			
Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
TQ	TQ1	0.88	0.84	0.85	0.76
	TQ2	0.84			
	TQ3	0.89			
OS	OS1	0.86	0.85	0.99	0.76
	OS2	0.93			
	OS3	0.83			
PU	PU1	0.88	0.79	0.81	0.71
	PU2	0.81			
	PU3	0.83			
US	US1	0.76	0.70	0.72	0.60
	US2	0.75			

Construct	Item	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
CI	US3	0.81	0.74	0.74	0.65
	CI1	0.83			
	CI2	0.79			
	CI3	0.81			

Furthermore, in Table 3, all values of AVE exceeded 0.50, proving sufficient convergent validity. All things considered, these results show that the measurement model meets the recommended quality criteria for PLS-SEM and offers a strong basis for the structural model's subsequent assessment. Establishing a reliable and valid measurement model is crucial in digital health studies, as it guarantees that theoretical constructs, not measurement mistakes, are reflected in the inferred structural relationships, thereby enhancing the credibility and interpretability of the research findings (J. Hair et al., 2022; J. F. Hair et al., 2026).

The HTMT was used to evaluate discriminant validity. Table 4 demonstrates that all HTMT values were below the suggested cutoff point of 0.90, showing adequate discriminant validity across components.

Table 4. Discriminant Validity

Construct	HL	TQ	OS	PU	US
Human Literacy	-				
Technology Quality	0.33	-			
Organizational Support	0.18	0.20	-		
Perceived Usefulness	0.45	0.48	0.40	-	
User Satisfaction	0.33	0.29	0.45	0.83	-
Continuance Intention	0.21	0.17	0.38	0.52	0.81

These results in Table 4 support the suggested measurement model's suitability and lessen the possibility of multicollinearity brought on by construct redundancy, thereby enhancing the robustness and interpretability of the subsequent structural model evaluation (M. Ali et al., 2026; J. Hair et al., 2022; J. F. Hair et al., 2026). Overall, the suggested validity and reliability standards were met by the measurement model for PLS-SEM analysis.

Structural Model Assessment

All predictor variables, namely Human Literacy (1.09), Technology Quality (1.02), Organization Support (1.00), Perceived Usefulness (1.08), and User Satisfaction (1.00), have VIF values that indicate no multicollinearity issues among the predictor constructs. From a methodological perspective, low collinearity enhances the stability and precision of parameter estimates, thereby enhancing the structural model's resilience and the legitimacy of subsequent hypothesis testing (J. Hair et al., 2022; J. F. Hair et al., 2026). Furthermore, the absence of multicollinearity is crucial in integrated HOT-Fit and TAM models, where certain constructs are theoretically interrelated yet must remain conceptually independent to accurately explain users' mHealth adoption behavior.

Table 5 shows that technology quality and organizational support explained 62% of the variance in perceived usefulness. Furthermore, perceived usefulness explained 58% of user satisfaction, while user satisfaction explained 52% of continuance intention.

Table 5. Structural Model Results

Construct Endogen	R^2
Perceived Usefulness	0.62
User Satisfaction	0.58
Continuance Intention	0.52

These findings in Table 5 indicate that the integrated HOT-Fit and TAM provide adequate predictive capability for explaining mHealth adoption among cadres. According to J. Hair et al., (2022) R^2 values exceeding 0.50 indicate moderate predictive accuracy in PLS-SEM, indicating that the

suggested model accounts for a significant amount of the variables affecting users' post-adoption perception and continuance intentions. The magnitude of the explainable variance, which is relatively high, also supports the conceptual integration of human, technological, and organizational dimensions in understanding digital health adoption within community-based disease surveillance programs (Olayiwola et al., 2026; Wittich et al., 2026).

Table 6 and Figure 3 show that the results of the hypothesis test demonstrated the statistical significance of each suggested association. Perceived usability was greatly impacted by human literacy ($\beta = 0.32$; $t = 2.87$; $p < 0.001$), indicating that cadres with better digital competencies are more capable of recognizing the practical benefits of health technologies.

Table 6. Hypothesis Testing

Hypothesis	Connection	β	t-value	f^2	p-value	Decission
H1	Human Literacy → Perceived Usefulness	0.32	2.87	0.16	<0.001	Accepted
H2	Technology Quality → Perceived Usefulness	0.35	3.43	0.20	<0.001	Accepted
H3	Organizational Support → Perceived Usefulness	0.44	5.37	0.32	<0.001	Accepted
H4	Perceived Usefulness → User Satisfaction	0.62	7.36	0.63	<0.001	Accepted
H5	User Satisfaction → Continuance Intention	0.57	5.38	0.49	<0.001	Accepted

These findings in Table 6 are consistent with the TAM, which states that user knowledge and competence facilitate positive evaluations of technology usability (Bastan et al., 2021; Lee et al., 2025). Digital literacy has been found to enhance user perceptions of usability and support technology adoption (Philpot et al., 2024; Yang et al., 2024). These results highlight the importance of strengthening cadres' digital competence through ongoing training and support to maximize perceived benefits and sustained use of mHealth apps in dengue prevention programs (Sitorukmi et al., 2025; Tembo et al., 2026).

As shown in Figure 3, perceived usability was strongly influenced by technology quality ($\beta = 0.35$; $t = 3.43$; $p < 0.001$), suggesting that system reliability, functionality, and ease of operation encourage users to perceive greater value in using the application. These findings support previous studies showing that perceived utility and long-term mHealth adoption are significantly influenced by system quality and technical performance (Wang et al., 2022; Ng & Kee, 2026). These results are also in line with the socio-technical approach, which highlights how user engagement in mHealth apps is greatly influenced by technology infrastructure, particularly in resource-constrained community settings (Ikwunne et al., 2023). This indicates that improving human literacy and the technical performance of the mHealth apps improved cadres' perceptions of the system's usability, particularly in low- and middle-income settings (Addotey-Delove et al., 2023; Kachimanga et al., 2024). From a practical perspective, these findings suggest that developers and community health centers should prioritize user-friendly interfaces, application stability, and low-bandwidth functionality when designing mHealth systems for cadres (Gyening et al., 2025; He et al., 2025).

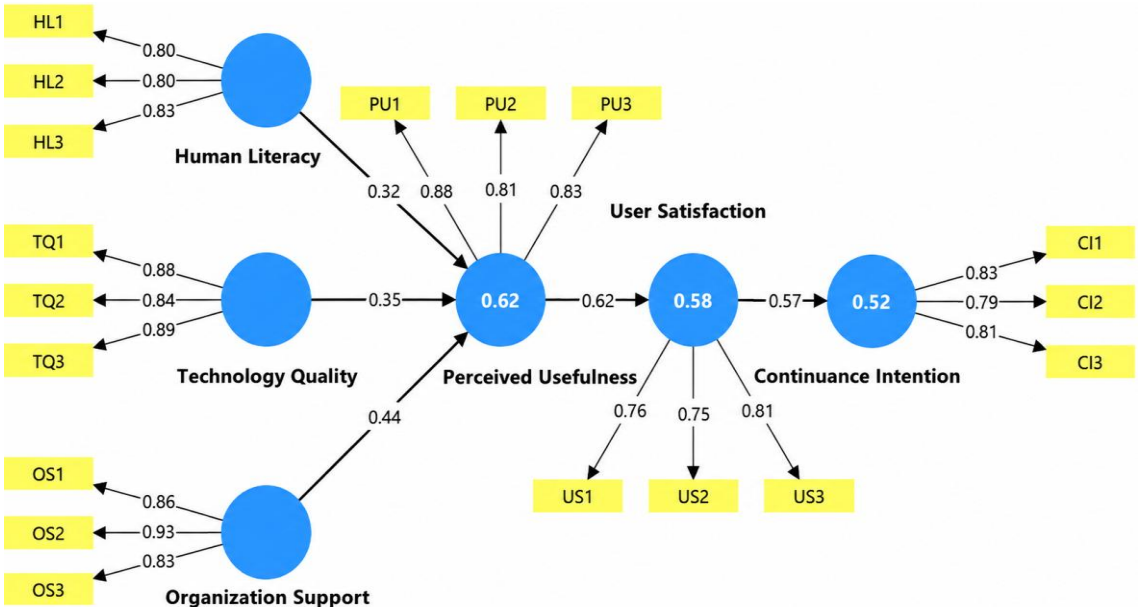

Figure 3. PLS – SEM Structural Model

In Figure 3, it can also be seen that organizational support showed a significant positive effect on perceived usability ($\beta = 0.44$; $t = 5.37$; $p < 0.001$). These findings suggest that support from a community health center and technical assistance positively contributed to cadres' evaluation of the app. This finding is consistent with the HOT-Fit framework, which highlights that organizational preparedness is just as important to the effective adoption of health information systems as technology quality. and continuous support (Sparidaens et al., 2023; Lim et al., 2025), on ongoing supervision, operational guidance, and technical facilitation (Alotaibi et al., 2025; Pattanaik et al., 2025). A supportive organizational environment can increase user trust and reduce perceived difficulties during technology adoption. (Feng & Feng, 2025). Previous studies have also reported that environmental and organizational support factors significantly contribute to positive user perceptions and the successful implementation of digital health systems. (Nie et al., 2023; Patel et al., 2025). Therefore, sustainable implementation strategies should include ongoing mentoring, refresher training, and a responsive technical support system for cadres (Charoensilpchai et al., 2026; Husnida et al., 2026).

Model Predictive Power Assessment (PLS Predict)

As presented in Table 7, the PLS-Predict analysis demonstrated satisfactory predictive performance of the proposed model. All endogenous constructs produced positive Q^2_predict values, including Perceived Usefulness (Q^2_predict = 0.33), User Satisfaction (Q^2_predict = 0.19), and Continuance Intention (Q^2_predict = 0.04). Furthermore, across all measurement indicators, the PLS-SEM model consistently yielded lower RMSE values compared to the linear model (LM) benchmark, demonstrating superior predictive accuracy. Overall, these findings indicate that the proposed integrated HOT-Fit and TAM model possesses adequate out-of-sample predictive capability for assessing mHealth adoption among dengue larvae monitoring cadres.

Table 7. PLS Predict Results

Construct	Item	$Q^2_{Predict}$	PLS RMSE	LM RMSE	Predictive Assessment
Perceived Usefulness	PU1	0.33	0.42	0.44	Better
	PU2		0.43	0.46	Better
	PU3		0.38	0.40	Better
User Satisfaction	US1	0.19	0.48	0.53	Better
	US2		0.48	0.52	Better
	US3		0.46	0.51	Better
Continuance Intention	CI1	0.04	0.49	0.51	Better
	CI2		0.38	0.41	Better
	CI3		0.50	0.53	Better

The PLSpredict results in Table 7 demonstrate that the proposed model possesses significant predictive capability; thus, the integrated HOT-Fit and TAM model not only explains the determinants of mHealth adoption but also predicts future observations with an acceptable level of accuracy. Recent methodological literature emphasizes that predictive assessment complements conventional explanatory evaluation in PLS-SEM by examining a model's practical utility in predicting new cases, rather than merely explaining observed relationships (J. Hair et al., 2022; Sarstedt et al., 2022). Consequently, this study's acceptable predictive performance provides empirical support for extending the structural model to develop AS, wherein validated path coefficients can be translated into a practical predictive index to identify healthcare professionals with varying levels of mHealth adoption and continuance intention. Additionally, model fit evaluation demonstrated acceptable fit indices, including SRMR = 0.07 and NFI = 0.91. This suggests that the model is not just statistically reliable for internal sample explanation but also has high precision and usability for prediction purposes in practical applications.

Acceptance Score Development (AS)

Following the PLS-SEM and PLSpredict analyses, a score was constructed using the standardized path coefficients obtained from the final structural model. The score was calculated as follows:

$$AS = (0.32 \times HL) + (0.35 \times TQ) + (0.44 \times OS) + (0.62 \times PU) + (0.57 \times US)$$

Where HL represents Human Literacy, TQ Technology Quality, OS Organizational Support, PU Perceived Usefulness, and US User Satisfaction.

CI was used as the criterion variable in Pearson correlation and regression analysis to assess the empirical validity of the suggested AS. The AS demonstrated a positive correlation with CI ($r = 0.488$, $p < 0.001$), confirming acceptable criterion-related validity. Furthermore, regression analysis showed that AS significantly predicted CI ($\beta = 0.498$, $t = 4.259$, $p < 0.001$; $F = 18.138$, $p < 0.001$). 43.8% of the variance in CI was explained by the model ($R^2 = 0.438$), suggesting that higher AS is associated with higher CI using the mHealth apps. Based on the regression analysis, CI can be predicted using the following equation:

$$CI = 0.566 + 0.672\ AS$$

The CI is predicted to rise by 0.672 units for every unit increase in AS. Collectively, this finding suggests that proposed AS processes have empirical validity and may serve as a practical predictor of sustained mHealth adoption among dengue larvae monitoring cadres.

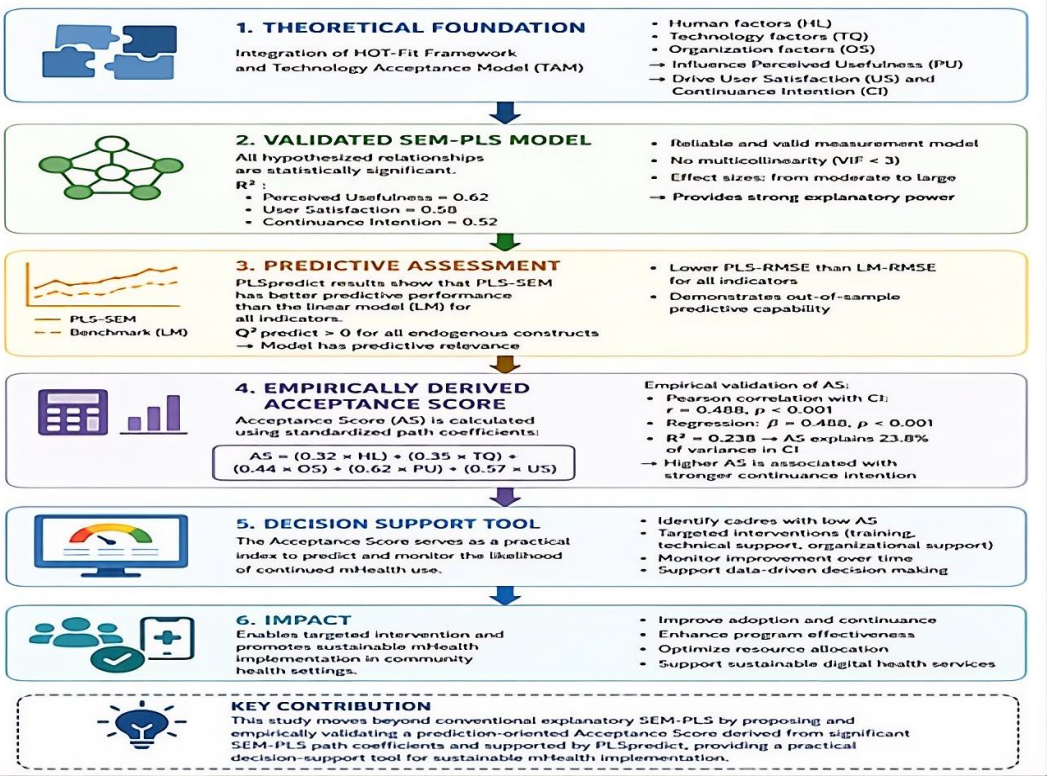

Figure 4. Prediction-Oriented Decision Support Framework for Sustainable mHealth Adoption

The development and validation of the AS extend the contribution of the integrated HOT-Fit and TAM model, moving beyond mere explanatory analysis toward practical prediction. Significant predictive relationships indicate that the proposed AS can serve as an empirically derived adoption index, reflecting users' overall readiness to sustain mHealth app usage. Recent methodological studies emphasize that integrating PLS-SEM explanatory analysis with predictive assessment provides stronger evidence for developing practical decision-support tools capable of identifying users who may require additional training or organizational support (J. Hair et al., 2022; Sarstedt et al., 2022). Thus, the proposed AS offers a practical mechanism for translating statistical findings into actionable information, thereby supporting monitoring, targeted interventions, and the implementation of evidence-based mHealth programs within the realm of public health. To synthesize the overall findings, Figure 4 demonstrates the conceptual significance of the study, showing how the integration of HOT-Fit and TAM, supported by PLS-SEM analysis and PLSpredict, yields empirically based acceptance scores for decision-support purposes. This framework demonstrates that the proposed model goes beyond merely explaining mHealth adoption; it offers a prediction-oriented approach to support evidence-based implementation and the sustainable use of digital health technology.

This study contributes theoretically by demonstrating the applicability of the HOT-Fit framework and TAM integration model within community-based dengue surveillance. While previous studies have largely focused on hospital information systems or patient-centered applications, the present study extends the use of these frameworks to cadre-based public health surveillance programs (Yang et al., 2024). The model also demonstrated satisfactory explanatory power despite the relatively small sample size. This suggests that a parsimonious PLS-SEM model may still provide meaningful insights in exploratory digital health implementation studies involving community health workers. Additionally, the study reinforces the importance of combining human, technological, and organizational perspectives when evaluating mHealth systems, particularly in developing-country settings where socio-technical barriers remain substantial (Ikwunne et al., 2021, 2023; Ooi et al., 2024).

Going beyond conventional explanatory PLS-SEM analysis, this study proposes a replicable methodological framework that integrates PLS-SEM, PLSpredict, and empirical validation to construct an adoption score. Unlike traditional latent variable analysis, this proposed framework transforms validated standardized path coefficients into a weighted adoption index, which is subsequently validated using correlation and regression analyses. This approach extends the scope of PLS-SEM from explanatory modeling to prediction-oriented research and provides a practical methodology for developing an empirically based adoption index in digital health research (J. Hair et al., 2022; Sarstedt et al., 2022).

This proposed acceptance score provides a simple, evidence-based decision-support tool to evaluate the likelihood of sustained mHealth adoption among dengue larvae monitoring cadres. Public health organizations can use this score to identify cadres requiring additional digital literacy training, technical assistance, or organizational support, thereby enabling more targeted interventions and efficient resource allocation. Furthermore, this acceptance score can facilitate the routine monitoring and evaluation of mHealth implementation and boost the long-term viability of community-based dengue surveillance programs by supporting data-driven decision-making.

This study offers several significant advantages. First, it integrates the HOT-Fit framework with the TAM, thereby providing a comprehensive perspective to explain mHealth adoption among dengue larvae monitoring cadres. Second, unlike conventional PLS-SEM studies that primarily focus on explaining relationships between variables, this study extends the analysis by employing PLSpredict to evaluate out-of-sample predictive performance and by developing an empirically validated acceptance score as a practical decision-support tool. This integrated analytical framework enhances the study's theoretical and practical contributions by translating statistical findings into a predictive model applicable to real-world situations. However, there are a number of limitations that need to be noted. First, the causal inference in this study does not allow for an assessment of changes in user acceptance over time. Second, this study focused on dengue larvae monitoring cadres in a specific geographic area; thus, the generalizability of the findings to other populations or healthcare contexts may be limited. Third, although the proposed acceptance score demonstrates significant predictive validity, its predictive performance requires external validation using an independent dataset and comparison with more advanced machine learning approaches before it can be more widely implemented. Therefore, future research employing longitudinal and multicenter designs, as well as external validation, is recommended to strengthen the generalizability and predictive robustness of the proposed model.

CONCLUSION

This study demonstrates that integrating the HOT-Fit and TAM frameworks provides a robust approach to explaining and predicting mHealth adoption among cadres monitoring dengue larvae. User literacy, technology quality, and organizational support significantly enhance perceived usefulness and user satisfaction, which in turn drives the continuance intention to use the mHealth apps. The structural model exhibits moderate explanatory and predictive performance, supported by satisfactory R^2 and PLS-Predict results, indicating that the proposed framework possesses strong capabilities for both explanatory purposes and out-of-sample prediction. Based on these findings, the study develops an empirically derived acceptance score. This score is generated from validated PLS-SEM path coefficients and subsequently verified through correlation and regression analyses. The proposed score demonstrates significant predictive capability for continuance intention to use mHealth apps, extending PLS-SEM from explanatory modeling to a practical predictive tool that supports decision-making. From a practical perspective, the acceptance score can assist public health organizations in identifying public health personnel who require additional training, technical assistance, or organizational support to enhance the sustainability of mHealth implementation. Future research needs to externally validate the proposed acceptance score using larger and more diverse populations, evaluate its predictive performance through machine learning approaches, and examine its application across various digital health programs and diverse public health settings.

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AUTHOR CONTRIBUTIONS

All authors made substantial contributions to this research and approved the final version of the manuscript. Conceptualization, AS and BSS; Supervision, AS and BSS; Project Administration, AS; Methodology, AS and BSS; Formal Analysis, AS and DIM; Investigation, AS; Data Curation, AS and BSS; Visualization, KSN and DIM; Software, AS and KSN.; Writing – Original Draft Preparation, AS and KSN.; Writing & Editing, AS and DIM.; Validation, AS., KSN.,DIM and BSS.; Resources, AS and DIM; Funding Acquisition, AS. Data Collection, AS; Advanced Analysis, AS and KSN; English Writing and Paraphrase, AS and DIM.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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