RESEARCH ARTICLE **Open Access**

Gema Lingkungan Kesehatan
Vol. 24, No. 4 (2026), pp 653-665
e-ISSN 2407-8948 p-ISSN 16933761
Doi: https://doi.org/10.36568/gelinkes.v24i4.574 *Journal Homepage: https://gelinkes.poltekkes-surabaya.ac.id/*

Factors Associated with Cadre Performance in mHealth Adoption: An Integrated HOT-Fit and TAM Approach

Agus Sugiharto[1,5*], Khansa Shafiqa Nahdah[2], Dede Irving Maryanto[3], Boy Subirosa Sabarguna[4]

[1] Department of Community Medicine, Faculty of Medicine, Universitas Indonesia, Jakarta, Indonesia
[2] Faculty of Public Health, Universitas Indonesia, Depok, Indonesia
[3] Faculty of Pharmacy, Universitas Pancasila, Jakarta, Indonesia
[4] Faculty of Medicine, Hang Tuah University, Surabaya, Indonesia
[5] Health Policy Management and Epidemiology Research Group, Indonesia

*Correspondence: agus.sugiharto@ui.ac.id

ABSTRACT

Digital transformation through mobile health (mHealth) is increasingly being utilized to strengthen community-based dengue fever (DHF) surveillance, but evidence on factors associated with cadre performance remains limited. This study aims to analyze the association between Human Literacy (HL), Technology Quality (TQ), Organizational Support (OS), Perceived Usefulness (PU), User Satisfaction (US), Continuance Intention (CI), and the Cadre Performance Index (CPI) using an integration of the Human, Organization, and Technology-Fit (HOT-Fit) and Technology Acceptance Model (TAM) framework. This cross-sectional design involved 60 dengue larval-monitoring cadres recruited through voluntary online convenience sampling in two Community Health Centers in Central Jakarta between April and July 2023. The 18-item questionnaire was piloted among 30 cadres. The available pilot output showed a combined six-construct Cronbach's alpha of 0.932 (standardized alpha 0.940) and corrected item-total correlations of 0.665–0.923. Pearson correlation, group comparisons, and multiple linear regression were conducted in SPSS. The regression model showed high in-sample explanatory power (R^2 = 0.949; adjusted R^2 = 0.938; F = 90.946; $p < 0.001$). CI had the largest standardized independent association with CPI (β = 0.451; $p < 0.001$), followed by PU (β = 0.176; p = 0.031), HL (β = 0.168; p = 0.001), US (β = 0.166; p = 0.043), and education level (β = 0.152; p = 0.011). The findings identify factors associated with cadre performance and provide a basis for future longitudinal and structural modelling of sustainable mHealth use.

Keywords: Cadre performance index; Community-based surveillance; Mobile health; HOT-Fit; Technology Acceptance Model.

INTRODUCTION

Dengue hemorrhagic fever (DHF) is still one of the biggest global public health issues, especially in tropical and subtropical areas. The incidence and transmission of this disease have grown during the past 20 years due to growing urbanization, population movement, climate change, and the development of vector habitats (Dehghani & Kassiri, 2021; Pratama & Lugito, 2017; Ramadhani, 2021). Millions of cases of dengue occur each year, putting a heavy burden on health systems, especially in low- and middle-income nations, and about half of the world's population is at risk of contracting the disease (Castro et al., 2017; Shah et al., 2020). This circumstance shows that good monitoring systems, early detection, and sustained vector control through active community involvement are all necessary for dengue control; case care alone is not sufficient (Omerovic, 2022; WHO, 2023).

A key element of effective dengue control in many endemic nations, including Indonesia, is community involvement. *Juru Pemantau Jentik* (*Jumantik*) cadres, a community health volunteer program that is in charge of household larval surveillance and dengue prevention, community education, and reporting monitoring results as a foundation for vector control programs, support community-based dengue surveillance in Indonesia (Rasyid Ridha et al., 2023; Sulistyawati et al., 2020). It has been demonstrated that the presence of cadres improves surveillance coverage and facilitates the early identification of possible outbreaks. However, there are still a number of issues that community-based surveillance systems must deal with, including manual recording, delayed reporting, variable data quality, and poor coordination between facilities and health professionals. These obstacles may lessen the efficacy of response and cadres' performance in

dengue control initiatives (Byrne & Nichol, 2020; McGowan et al., 2022; World Health Organization, 2023).

Opportunities to address these issues through the application of mobile health (mHealth) are presented by developments in digital transformation. With better data quality, real-time reporting, and evidence-based cadre performance, the WHO views digital transformation as a vital tactic for bolstering health systems (World Health Organization, 2022, 2023). For dengue control, mHealth enables faster, more accurate, and more comprehensive submission of mosquito larval monitoring results while also enhancing collaboration among medical professionals. Numerous studies have demonstrated that mHealth can enhance both the standard of public health services and the productivity of community health workers. However, user preparedness, organizational support, system quality, and the sustainability of application use in everyday activities all have an impact on the success of mHealth implementation, in addition to technology availability (Déniz García et al., 2023; Erku et al., 2023; Jacob et al., 2020). mHealth provides an opportunity to improve timeliness, completeness, and accessibility of surveillance information. However, implementation depends not only on technology availability but also on user capability and perceived usefulness, organizational support, system quality, satisfaction, and continued use. An evaluation strategy that incorporates organizational, human, technological, and user behavioral factors is required to comprehend this complexity.

The Human, Organization, and Technology-Fit (HOT-Fit) and the Technology Acceptance Model (TAM) address complementary levels of this problem. HOT-Fit emphasizes the fit among human, organizational, and technology conditions in health information-system implementation, whereas TAM focuses on user perceptions of usefulness and acceptance-related responses. Continuance Intention represents a post-adoption behavioral-intention construct relevant to sustained use. Integrating these perspectives allows the study to examine contextual, technological, human factors, and acceptance-related correlates within one analytical framework. The integration is therefore complementary rather than a claim that either model is insufficient on its own.

Even though the amount of research on mHealth implementation is still increasing, the majority of it still focuses on system quality, user approval, or the degree of technological adoption as markers of implementation success. Prior research has typically assessed organizational, technological, or human factors independently, failing to explain how these aspects interact to affect user performance and sustained app use (Or et al., 2022). Additionally, there is still a dearth of empirical data regarding the use of mHealth by mosquito larva monitoring cadres in poor nations like Indonesia (Tahir et al., 2023). By combining HOT-Fit and TAM to explain the mechanisms of effective mHealth implementation through continuance intentions and connecting them to the Cadre Performance Index (CPI) as a measure of cadre performance in carrying out community-based dengue surveillance, this study closes this gap. This strategy is expected to increase understanding of the variables that are associated with the effectiveness of mHealth implementation in community-based dengue surveillance initiatives. In light of this context, the purpose of this study was to examine the association of Human Literacy (HL), Organizational Support (OS), and Technology Quality (TQ), Perceived Usefulness (PU), User Satisfaction (US), and Continuance Intentions (CI), and selected sociodemographic characteristics with CPI among dengue larval-monitoring cadres.

METHODS

Study Design and Setting

This study integrates the HOT-Fit framework and the TAM to assess cadres' use of a mHealth application using an analytical observational design and a cross-sectional methodology, with the research workflow shown in Figure 1. To identify factors related to cadres' performance in using the mHealth application, the cross-sectional design was chosen because it allows the assessment of respondent characteristics, perceptions regarding mHealth implementation, and the relationships between study variables within a single observation period (Cvetkovic-Vega et al., 2021; Vandenbroucke et al., 2021). From April to July 2023, the research was carried out at the Bungur Community Health Center in Senen and the Kemayoran Community Health Center in Central Jakarta, Indonesia. Both settings used the mHealth application within community-based mosquito larva surveillance activities.

Study Population and Data Collection

Every cadre in the study region who was actively using the mHealth application made up the study population. Active cadres who were willing to take part in the study and had regularly utilized the application for dengue fever surveillance were eligible. Cadres who did not participate in the study or who did not complete the questionnaires were not included. In this study, a convenience sampling method using an online questionnaire was used. This study's final analysis includes 60 respondents. Participation was voluntary; therefore, respondents may have been those who were more active in or comfortable with digital application use.

Research Variables and Conceptual Framework

The HOT-Fit framework and TAM are used in this study to assess cadres' use of a mHealth application. Aspects of human, technological, organizational, and user acceptance are represented by the research variables HL, TQ, OS, PU, US, and CI. The CPI is the dependent variable used to evaluate cadre performance in supporting DHF surveillance activities. TAM constructs were used to explain technology acceptance based on PU and user behavior (Al-Qaysi et al., 2021; Bastan et al., 2021; Ishengoma, 2024; Sparidaens et al., 2023), while HOT-Fit constructs were chosen based on the framework's capacity to assess the success of health information system implementation across human, organizational, and technological

dimensions (Abdulaziz, 2021; Ahmetoglu & Cob, 2022; Bastan et al., 2021; Zhai et al., 2022). As a crucial sign of a successful mHealth implementation, Continuance Intention was added to evaluate the durability of application usage after the initial adoption phase (Veronika et al., 2025).

Instrument Development

A structured questionnaire was developed by adapting measures used in previous studies and contextualizing them for *Jumantik* cadres using mHealth. The instrument contained 18 Likert-scale items and 6 constructs, with three items for each construct: HL, TQ, OS, PU, US, and CI. Sources retained from the original instrument development were Ahmetoglu and Cob (2022), Bastan et al. (2021), Zhai et al. (2022), Al-Qaysi et al. (2021), and Sparidaens et al. (2023), according to the construct. Responses ranged from 1 (strongly disagree) to 5 (strongly agree). The CPI was constructed as the equal-weight mean of five standardized performance indicators reporting timeliness, report completeness, consistency in application usage, monitoring frequency, and household screening coverage. The CPI was taken from routine program records for the same cadres, and each indicator was standardized to a 0 to 100 scale before averaging. Using program record data for the CPI represented documented cadre performance and reduced reliance on self-reported performance outcomes.

Pilot Validity and Reliability

The validity and reliability of the research instrument were validated using 30 cadres before primary data collection. The Pearson Product-Moment correlation between individual item scores and the overall construct score was used to examine validity. If an item fulfilled the necessary minimum correlation value and showed a significant correlation coefficient ($p < 0.05$), it was considered legitimate (Wijaya & Kloping, 2021). The Cronbach's Alpha coefficient was used to assess instrument reliability; a result of ≥0.70 denotes strong internal consistency (Izah et al., 2023). The six construct scores were combined in one reliability analysis. The combined six-construct scale showed Cronbach's Alpha of 0.932 and standardized alpha of 0.940. Corrected item-total correlations range from 0.665 to 0.923, as shown in Table 1. The pilot correlation matrix showed statistically significant positive associations among the six constructs' scores ($p \leq 0.006$), with the highest correlation for TQ-OS ($r = 0.933$) and TQ-PU ($r = 0.905$). The instrument is considered reliable and suitable for use in future research.

Table 1. Pilot Instrument Assessment (n=30)

Construct	Code	Questionnaire item	Corrected item–total correlation	Cronbach's α if deleted
HL	HL1	I can use applications without assistance.	0.665	0.945
	HL2	I understand the features of the application easily.		
	HL3	I can solve minor technical problems while using the application.		
TQ	TQ1	Easy-to-use application for mosquito larvae monitoring activities.	0.884	0.910
	TQ2	The application runs stably and rarely experiences interruptions.		
	TQ3	The application can be accessed quickly when used.		
OS	OS1	The organization provides support for the use of the application.	0.851	0.913
	OS2	I got enough training to use the application.		
	OS3	Technical assistance was available when I had difficulties.		
PU	PU1	The app simplifies the process of reporting mosquito larvae inspection results.	0.923	0.901
	PU2	Using the app makes my mosquito larvae monitoring work faster.		
	PU3	The app helps monitor data more effectively.		
US	US1	I'm satisfied using this application.	0.806	0.919
	US2	This application meets my surveillance needs.		
	US3	I've had a pleasant experience using this application.		
CI	CI1	I intend to continue using this application.	0.763	0.924
	CI2	I will recommend this application to other cadres.		
	CI3	I want this application to continue being used in surveillance activities.		

Data Collection

An online survey using the Google Forms platform was used to collect data between April and July of 2023. Cadre coordinators or employees from Community Health Centers participating in the DHF control program sent the questionnaire link to cadres. Participants received information about the study's goals and advantages, data confidentiality, and electronic informed consent. One response per participant was allowed, and incomplete or non-compliant responses were excluded.

Data Analysis

IBM SPSS Statistics version 25 was used for the data analysis. Descriptive statistics included means, standard deviations, frequencies, and percentages. The Pearson correlation was used to examine associations among HL, TQ, OS, PU, US, CI, and CPI. One-Way ANOVA was used for age, education, and length-of-service groups, and an independent-samples t-test was used for occupation. Tukey HSD was used for significant ANOVA results. Multiple linear regression estimated independent associations with CPI using 10 predictors: age group, education level, time as cadre, occupation, HL, TQ, OS, PU, US, and CI. The assumption of multicollinearity was assessed before

performing the multiple linear regression analysis. Variance inflation factor (VIF) values were less than 10, and a significance level of $p < 0.05$ was applied to all statistical tests (James et al., 2021; Montgomery et al., 2021).

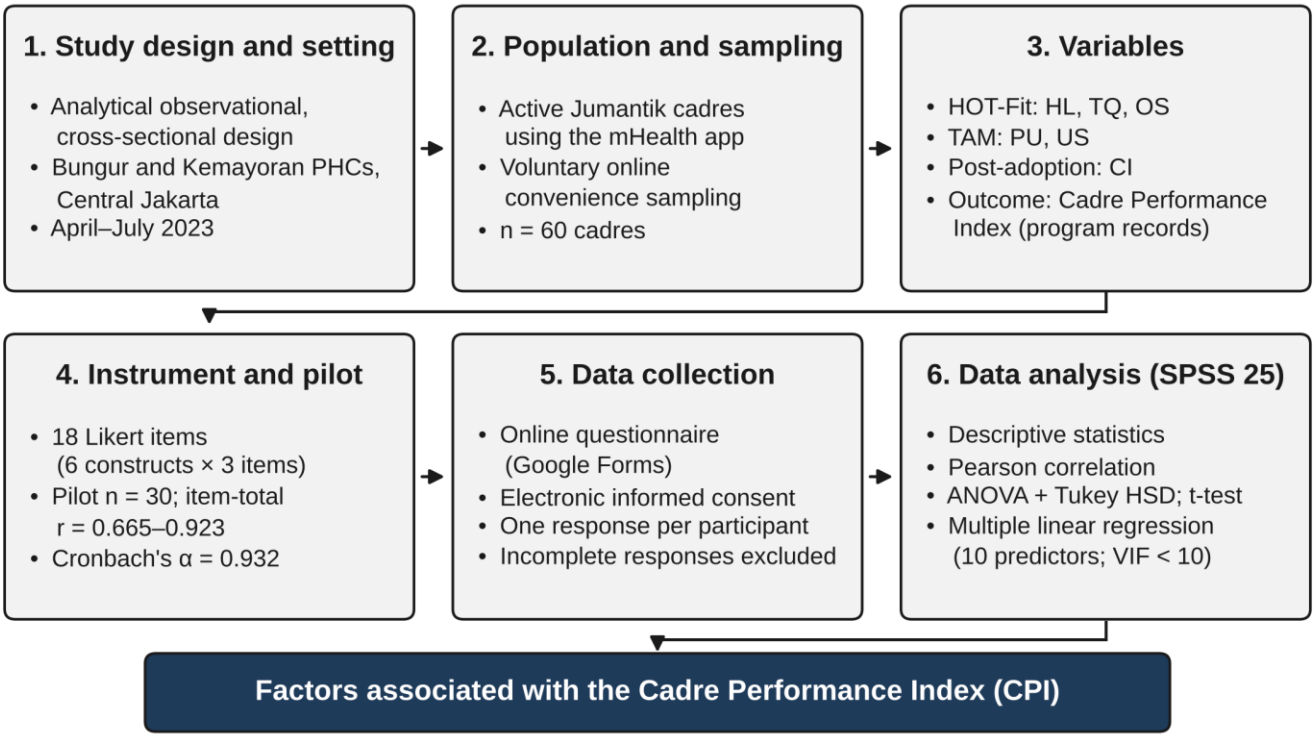


Figure 1. Research flow diagram

Ethical Approval

The Ethical Committee of Medicine at Universitas Indonesia granted ethical approval for this study. The ethical approval number is KET-509/UN2.F1/ETIK/PPM.00.02/2022. Every research process was carried out in compliance with relevant ethical norms, such as respect for respondent autonomy, confidentiality of data, and voluntary participation. All respondents gave electronic informed consent and were made aware of the goals and methods of the study before filling out the questionnaire. Every piece of information gathered was kept private, anonymised during processing, and utilized only for the study.

RESULTS AND DISCUSSION

Respondent Characteristics

A total of 60 cadres participated in this study, as shown in Table 2; all respondents (100%) were female. Regarding age groups, the majority of respondents were aged 30–45 years (n=40; 66.7%), followed by the >45 years age group (n=11; 18.3%), while 9 respondents (15.0%) were under 30 years of age. In terms of education level, the majority of respondents had completed senior high school (n=47; 78.3%), while 9 individuals (15.0%) had a junior high school education, and only 4 individuals (6.7%) had a college education background. Regarding their experience as cadres, nearly half had served for 1–5 years (46.7%), followed by those who had served for more than 5 years (40.0%), while 13.3% had less than 1 year of experience. Concerning employment status, the majority of respondents were housewives (n=51; 85.0%), while 9 individuals (15.0%) worked as traders or were self-employed.

According to respondent characteristics, most cadres are women between the ages of 30 and 45 who are of working age, have completed high school, and have worked as cadres for more than a year. The typical makeup of cadres engaged in dengue prevention initiatives, where women predominate in household and environmental health activities, is reflected in this demographic profile. Additionally, the fact that a large number of respondents had previous field experience indicates that they were already used to regular larval monitoring activities; as a result, they were able to offer well-informed evaluations of the mHealth application rather than depending just on first impressions. As a result, the study sample is made up of people who have actually used digital health interventions in regular, community-based dengue surveillance operations. In addition to reducing variability resulting from non-technical factors, relatively uniform demographic data, especially about gender and employment, might also facilitate further study to better capture the impact of organizational factors and technology acceptance on cadre performance.

Table 2. Characteristics of Respondents (n=60)

Characteristics	Category	n	%
Gender	Female	60	100
Age Group	< 30 years	9	15
	30 – 45 years	40	66.7
	>45 years	11	18.3

Characteristics	Category	n	%
Level of Education	Junior high school	9	15
	Senior high school	47	78.3
	College	4	6.7
Time as a Cadre	< 1 year	8	13.3
	1 – 5 years	28	46.7
	>5 years	24	40
Occupational	Housewife	51	85
	Trader/Entrepreneur	9	15

Distribution of HOT-Fit, TAM Domains, CI, and CPI

The scores for each research domain, HL, TQ, OS, PU, US, CI, and the CPI are shown in Table 3 along with descriptive data. Data from 60 respondents were used to analyze each variable. All domain data had a p-value > 0.05, suggesting that the data were normally distributed and satisfied the parametric assumptions for additional analysis, according to a normality test using the Kolmogorov-Smirnov method.

Table 3. Descriptive Statistics for HOT-Fit, TAM Domain Scores, CI, and CPI (n = 60)

Domain	Minimum Score	Maximum Score	Mean ± SD
HL	9	15	12.03 ± 1.64
TQ	9	14	11.37 ± 1.12
OS	9	14	11.53 ± 1.23
PU	9	15	11.78 ± 1.37
US	8	12	10.12 ± 1.19
CI	8	12	9.67 ± 1.13
CPI	87	92	90.04 ± 1.65

Descriptive analysis showed that HL had the highest mean score (12.03 ± 1.64), followed by PU (11.78 ± 1.37), OS (11.53 ± 1.23), and TQ (11.37 ± 1.12). In contrast, US (10.12 ± 1.19) and CI (9.67 ± 1.13) demonstrated comparatively lower mean scores, although all domains remained within the positive response range. The CPI was consistently high (90.04 ± 1.65), indicating generally favorable performance among respondents. The high HL score indicates that cadres were typically capable of using the mHealth application, according to the data. The relatively lower CI, however, suggests that continued application use is not guaranteed by technological capabilities alone. This result implies that sustaining long-term involvement in everyday practice is now the primary problem rather than initial technology adoption. Similar findings from earlier research have shown that, whereas digital capacity promotes early mHealth adoption, PU, OS, US, and favorable post-adoption experiences are more important for sustained use (Kılıç & Durmaz, 2026; Ng & Kee, 2026).

The current results are in line with earlier research demonstrating that favorable opinions of mHealth do not always result in long-term technology adoption. Similar trends have been observed among community health professionals, where organizational support, workflow integration, and perceived value, rather than just technical proficiency, had an impact on long-term application use (Alzghaibi, 2025a; Elepaño et al., 2026; Kansiime et al., 2024). The consistency of these results suggests that maintaining the use of mHealth in many community health settings, including dengue surveillance programs, remains a common difficulty. These results suggest that increasing users' technical proficiency is not enough for mHealth implementation to be successful. To encourage persistent technology use, it is crucial to strengthen support from the organization through consistent training, encouraging supervision, performance reviews, and application integration into normal program operations. According to recent research emphasizing the significance of ongoing organizational support for successful digital health implementation, such tactics are anticipated to increase the efficacy and sustainability of community-based dengue prevention programs (Mazariego-Longoria et al., 2026; Okafor et al., 2026; Rivera et al., 2023).

Correlation among HOT-Fit, TAM, CI, and CPI

As shown in Table 4 and Figure 2, correlation values ranging from 0.563 to 0.908, Pearson correlation analysis showed that all HOT-Fit domains, TAM constructs, and the CPI were positively and strongly associated (all p < 0.001).

Table 4. Pearson correlation between HOT-Fit domains, TAM, CI, and CPI (n = 60)

Variable	HL	TQ	OS	PU	US	CI
	r	r	r	r	r	r
HL						
TQ	0.613**					
OS	0.658**	0.879**				
PU	0.617**	0.828**	0.858**			
US	0.579**	0.563**	0.581**	0.628**		
CI	0.575**	0.567**	0.582**	0.655**	0.908**	
CPI	0.741**	0.770**	0.789**	0.810**	0.867**	0.896**

US and CI showed the highest connection (r = 0.908), followed by CI and CPI (r = 0.896) and TQ and OS (r = 0.879). These results show that consistent application use and improved cadre performance are strongly correlated with favorable user experiences, which are bolstered by a dependable technological and organizational environment.

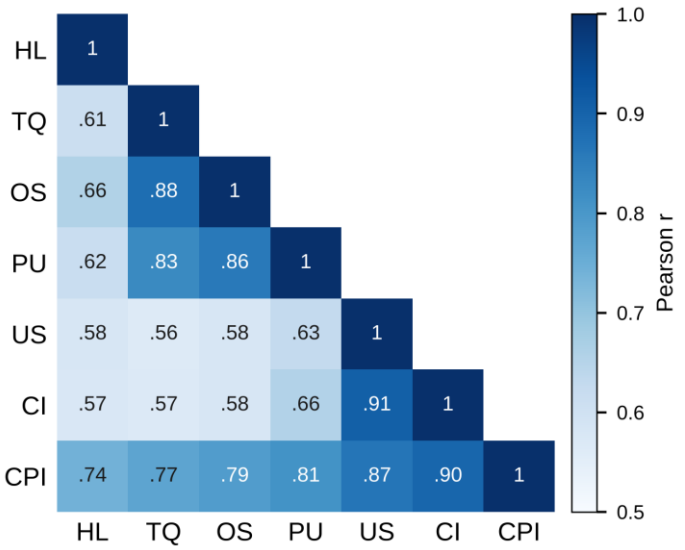


Figure 2. Correlation matrix (Pearson r) among HOT-Fit domains, TAM constructs, CI, and CPI (n = 60; all p < 0.001)

The HOT-Fit paradigm and the TAM, which contend that human, technical, and organizational elements interact to produce successful digital health deployment, are supported by the observed correlation pattern. Specifically, the high correlation between the US and CI indicates that the US is crucial to maintaining mHealth use after initial acceptance. Recent systematic studies have revealed similar results, concluding that PU, US, OS, and integration into routine workflows are important factors that influence community health professionals' continuing use of digital health (Kılıç & Durmaz, 2026; Ng & Kee, 2026). The significance of post-adoption support strategies in community-based dengue surveillance programs is further highlighted by the strong correlation between CI and CPI, which suggests that sustaining long-term engagement with the application may have a greater impact on enhancing cadre performance than technology acceptance alone.

Differences in HOT-Fit, TAM, and CPI across Sociodemographic Characteristics

A bivariate study assessed variations in the TAM, the CPI, and the HOT-Fit domain scores according to the sociodemographic traits of the respondents, as shown in Table 5.

Age and occupation did not significantly affect any of the areas (all $p > 0.05$), suggesting that respondents' opinions of mHealth apps were largely consistent. In contrast, education level was significantly associated with all study domains: HL ($F = 10.664$), TQ ($F = 29.501$), OS ($F = 35.834$), PU ($F = 53.840$), US ($F = 14.976$), CI ($F = 16.049$), and CPI ($F = 22.549$) (all $p < 0.001$). Similarly, length of service as a cadre was significantly associated with all domains (HL: $F = 12.077$; TQ: $F = 5.525$; OS: $F = 7.473$; PU: $F = 5.741$; US: $F = 4.685$; CI: $F = 5.438$; CPI: $F = 7.727$; all $p < 0.05$), with scores tending to be higher among cadres who had served for more than five years. These results imply that mHealth acceptance is more associated with education and professional experience than with age and occupation. Higher-educated cadres are more likely to use mHealth apps because they have greater digital literacy, comprehension of technology, and perceptions of its advantages. These findings align with the TAM and the HOT-Fit Framework, which identify user capacity as a critical factor in the successful deployment of health information systems (Asnadi et al., 2025; Mustafa et al., 2024; Rampinelli et al., 2026). Additionally, cadres with more than five years of experience scored higher in every HOT-Fit, TAM, and CPI category, suggesting that field experience enhances one's capacity to apply programs, comprehend workflows, and sustain technology utilization in practice. According to studies by Jeilani and Hussein (2025), Shin et al. (2026), and Ghaith et al. (2026), job experience plays a crucial role in the successful adoption and long-term viability of health technology. According to Wang et al. (2025) and Alzghaibi (2025b), user competency is more important for the successful implementation of mHealth than demographic factors, as evidenced by the negligible effects of age and occupation. Overall, these findings support the idea that boosting cadre capacity—particularly for cadres with less education and experience—through continual training, mentoring, and developing digital literacy is a crucial tactic to enhance mHealth implementation success and cadre performance.

Table 5. Bivariate Analysis of Study Across Sociodemographic Characteristics (n = 60)

Sociodemographic Characteristics	n	Total HL Score (Mean ± SD)	Total TQ Score (Mean ± SD)	Total OS Score (Mean ± SD)	Total PU Score (Mean ± SD)	Total US Score (Mean ± SD)	Total CI Score (Mean ± SD)	CPI Score (Mean ± SD)
Age Group								
<30 years	9	11.78±1.09	11.22±1.09	11.44±1.13	11.44±1.01	9.89±0.93	9.33±0.71	89.51±1.13
30–45 years	40	12.08±1.54	11.45±1.04	11.55±1.13	11.80±1.20	10.15±1.17	9.73±1.13	90.16±1.58
>45 years	11	12.09±2.34	11.18±1.47	11.55±1.69	12.00±2.10	10.18±1.54	9.73±1.42	90.07±2.25
Test statistic		F=0.126; p=.882	F=0.328; p=.722	F=0.027; p=.973	F=0.410; p=.666	F=0.190; p=.827	F=0.452; p=.639	F=0.552; p=.579
Level of Education								
Junior high school	9	10.44±1.51	9.56±0.73	9.56±0.73	9.44±0.53	8.56±0.73	8.22±0.44	87.64±0.70
Senior high school	47	12.15±1.40	11.62±0.77	11.77±0.87	12.04±0.86	10.32±1.02	9.83±0.99	90.34±1.37
College	4	14.25±1.50	12.50±1.29	13.25±0.50	14.00±0.82	11.25±0.96	11.00±0.82	92.00±0.00
Test statistic		F=10.664***; p<.001	F=29.501***; p<.001	F=35.834***; p<.001	F=53.840***; p<.001	F=14.976***; p<.001	F=16.049***; p<.001	F=22.549***; p<.001
Time as a Cadre								

Sociodemographic Characteristics	n	Total HL Score (Mean ± SD)	Total TQ Score (Mean ± SD)	Total OS Score (Mean ± SD)	Total PU Score (Mean ± SD)	Total US Score (Mean ± SD)	Total CI Score (Mean ± SD)	CPI Score (Mean ± SD)
<1 year	8	10.13±1.55	10.63±1.19	10.63±1.19	10.88±1.36	9.25±0.89	8.63±0.74	88.45±1.29
1–5 years	28	11.86±1.38	11.14±1.08	11.25±1.24	11.50±1.35	9.96±1.32	9.64±1.13	89.86±1.62
>5 years	24	12.88±1.36	11.88±0.95	12.17±0.92	12.42±1.14	10.58±0.93	10.04±1.04	90.78±1.38
Test statistic		F=12.077***; p<.001	F=5.525**; p=.006	F=7.473**; p=.001	F=5.741**; p=.005	F=4.685*; p=.013	F=5.438**; p=.007	F=7.727**; p=.001
Occupation								
Housewife	51	12.16±1.65	11.45±1.12	11.61±1.22	11.84±1.35	10.20±1.17	9.71±1.15	90.12±1.62
Trader/Entrepreneur	9	11.33±1.41	10.89±1.05	11.11±1.27	11.44±1.51	9.67±1.32	9.44±1.01	89.60±1.89
Test statistic		t=1.404; p=.166	t=1.400; p=.167	t=1.121; p=.267	t=0.805; p=.424	t=1.231; p=.223	t=0.637; p=.527	t=0.871; p=.387

Note: Data are presented as the Mean ± Standard Deviation (SD). Age, education level, and length of service were analyzed using One-Way ANOVA (*F*-values). Occupation was analyzed using the Independent Samples *t*-test (*t*-values). *p<.05, **p<.01, ***p<.001. Gender is excluded as all participants were female (100%).

A Tukey HSD post-hoc test was used to identify particular groups showing notable variations in order to further investigate important findings relating to the variables of education level, as shown in Table 6, and time as a cadre, as shown in Table 7.

Table 6. Post-Hoc Tukey HSD Multiple Comparisons for Level of Education (n = 60)

Variable	Comparison	Mean Diff	Std. Error	p-value	95% Confidence Interval
HL Score	Junior high school vs Senior high school	-1.704	0.517	0.005*	[-2.9478, -.4612]
	Junior high school vs College	-3.006	0.853	0.001*	[-5.0589, -1.7522]
	Senior high school vs College	-2.101	0.740	0.017*	[-3.8808, -.3213]
TQ Score	Junior high school vs Senior high school	-2.061	0.290	<0.001*	[-2.7605, -1.3625]
	Junior high school vs College	-2.944	0.480	<0.001*	[-4.0989, -1.7900]
	Senior high school vs College	-0.883	0.416	0.094	[-1.8836, .1176]
OS Score	Junior high school vs Senior high school	-2.210	0.303	<0.001*	[-2.9383, -1.4825]
	Junior high school vs College	-3.694	0.500	<0.001*	[-4.8967, -2.4922]
	Senior high school vs College	-1.484	0.433	0.003*	[-2.5261, -.4420]
PU Score	Junior high school vs Senior high school	-2.598	0.298	<0.001*	[-3.3143, -1.8819]
	Junior high school vs College	-4.556	0.492	<0.001*	[-5.7384, -3.3727]
	Senior high school vs College	-1.967	0.426	<0.001*	[-2.9827, -.9322]
US Score	Junior high school vs Senior high school	-1.764	0.358	<0.001*	[-2.6251, -.9021]
	Junior high school vs College	-2.694	0.591	<0.001*	[-4.1173, -1.2716]
	Senior high school vs College	-0.931	0.512	0.173	[-2.0154, .1534]
CI Score	Junior high school vs Senior high school	-1.608	0.335	<0.001*	[-2.4127, -.8025]
	Junior high school vs College	-2.778	0.553	<0.001*	[-4.1075, -1.4481]
	Senior high school vs College	-1.170	0.479	0.046*	[-2.3227, -.0117]
CPI Score	Junior high school vs Senior high school	-2.692	0.457	<0.001*	[-3.7914, -1.5921]
	Junior high school vs College	-4.357	0.755	<0.001*	[-6.1717, -2.5394]
	Senior high school vs College	-1.664	0.654	0.036*	[-3.2380, -.0897]

Note: Tukey HSD test was used for post-hoc pairwise comparisons. *p < 0.05.

In every aspect, cadres with only a junior high school education performed significantly worse than those with a high school or college education ($p < 0.05$). Additionally, cadres with college degrees performed better on HL, OS, PU, CI, and the CPI than high school graduates. TQ and US, however, did not differ ($p > 0.05$). Overall, these findings demonstrate a steady rise in scores as education levels rise. These results demonstrate that education has a significant role in the adoption and use of mHealth. Higher-educated cadres are more likely to be digitally literate, comprehend technology, and see its advantages, which makes it easier for them to incorporate the app into their mosquito larva monitoring tasks. These findings support the Human component of the HOT-Fit Framework, which views user capacity as a critical factor in the successful implementation of health information systems (Alzghaibi, 2025b; Wang et al., 2025), and are consistent with the TAM, which claims that user capabilities influence perceived usefulness and the continued use of technology (Al-Jamili et al., 2026).

The fact that TQ and US did not differ between the high school and college groups implies that system quality and US are comparable once users complete secondary school. On the other hand, the remaining substantial differences in HL, PU, CI, and CPI indicate that, rather than just boosting users' assessment of system quality, higher educational attainment appears to improve users' capacity to convert favorable impressions of the system into sustained application use. These results are in line with studies showing that educational attainment and digital literacy are significant predictors of mHealth implementation success in community-based healthcare (Ghaith et al., 2026; Jeilani & Hussein, 2025; Shin et al., 2026). Therefore, in order to promote fairer adoption of

the technology, expanding the implementation of mHealth must be supported by training and mentorship that are appropriate for the cadres' educational level.

Table 7. Post-Hoc Tukey HSD Multiple Comparisons for Time as Cadres (n = 60)

Variable	Comparison	Mean Diff (I-J)	Std. Error	p-value	95% Confidence Interval
HL Score	<1 yr vs 1-5 yrs	-1.732	0.559	0.008*	[-3.0779, -.3863]
	<1 yr vs >5 yrs	-2.750	0.570	<0.001*	[-4.1205, -1.3795]
	1-5 yrs vs >5 yrs	-1.018	0.388	0.030*	[-1.9517, -.0840]
TQ Score	<1 yr vs 1-5 yrs	-0.518	0.418	0.435	[-1.5234, .4877]
	<1 yr vs >5 yrs	-1.250	0.427	0.013*	[-2.2740, -.2260]
	1-5 yrs vs >5 yrs	-0.732	0.290	0.038*	[-1.4299, -.0344]
OS Score	<1 yr vs 1-5 yrs	-0.625	0.446	0.347	[-1.6976, .4476]
	<1 yr vs >5 yrs	-1.542	0.454	0.004*	[-2.6339, -.4494]
	1-5 yrs vs >5 yrs	-0.917	0.309	0.012*	[-1.6609, -.1724]
PU Score	<1 yr vs 1-5 yrs	-0.625	0.509	0.441	[-1.8497, .5987]
	<1 yr vs >5 yrs	-1.542	0.518	0.012*	[-2.7878, -.2955]
	1-5 yrs vs >5 yrs	-0.917	0.353	0.031*	[-1.7658, -.0676]
US Score	<1 yr vs 1-5 yrs	-0.714	0.451	0.262	[-1.8008, .3722]
	<1 yr vs >5 yrs	-1.333	0.460	0.014*	[-2.4398, -.2269]
	1-5 yrs vs >5 yrs	-0.619	0.313	0.127	[-1.3729, .1349]
CI Score	<1 yr vs 1-5 yrs	-0.399	0.422	0.618	[-2.0342, .3042]
	<1 yr vs >5 yrs	-1.417	0.430	0.005*	[-2.4516, -.3817]
	1-5 yrs vs >5 yrs	-1.018	0.293	0.001*	[-2.0342, -.0015]
CPI Score	<1 yr vs 1-5 yrs	-1.414	0.598	0.055	[-2.8526, .0240]
	<1 yr vs >5 yrs	-2.333	0.609	0.001*	[-3.7980, -.8687]
	1-5 yrs vs >5 yrs	-0.919	0.415	0.077	[-1.9171, .0790]

Note: Tukey HSD test was used for post-hoc pairwise comparisons. *p < .05.

Across all domains, cadres with more than five years of experience consistently outperformed those with less than one year ($p < 0.05$). The group with more than five years of experience likewise showed better scores on HL, TQ, OS, PU, and CI when compared to cadres with one to five years of experience; however, differences in US and CPI were not statistically significant. Additionally, across all experience groups, HL was the only domain that demonstrated both incremental and substantial improvement. Overall, these findings show that a cadre's degree of mHealth acceptability and performance increases with experience. These results imply that cadres' comprehension, acceptance, and use of mHealth applications are improved by field experience. The idea of experiential learning, in which competence is developed via repeated practical experience, is supported by steady advances in HL (Kolb, 2015). Higher scores on TQ, OS, PU, and CI among seasoned cadres further suggest that lengthier program involvement leads to a steady development of technology adaptation and perceived application usefulness. These findings are consistent with studies that demonstrate how important user experience is to the effective deployment and sustained usage of health information systems (Ghaith et al., 2026; Jeilani & Hussein, 2025; Shin et al., 2026).

Even if technological adoption keeps rising, US and performance tend to plateau after a few years of use, as seen by the lack of differences in US and CPI between cadres with one to five years of experience and those with more than five years. The Expectancy Confirmation Model explains that satisfaction develops early in use and then stays relatively stable (Dai et al., 2025; Yusuf et al., 2026). This is consistent with this pattern. Additionally, research indicates that user experience plays a role in sustained adoption of mHealth (Ghaith et al., 2026; Jeilani & Hussein, 2025; Shin et al., 2026). These results support the Human component of the HOT-Fit Framework, which highlights the significance of building user capacity through training, mentoring, and hands-on learning to enhance cadres' performance and the success of mHealth deployment.

Multiple Linear Regression

After adjusting for sociodemographic factors and supporting domains, a multiple linear regression analysis was performed to identify the main predictors that have the greatest impact on the CPI.

Tables 8 and 9 show that multiple linear regression analysis included 10 predictors, and Figure 3 summarizes the adjusted regression coefficients together with the bivariate correlations of each domain with the CPI. The model was statistically significant ($F = 90.946$; $p < 0.001$) with $R = 0.974$, $R^2 = 0.949$, and adjusted $R^2 = 0.938$. This means that approximately 94.9% of the variation in the CPI can be explained by the combination of sociodemographic characteristics, HOT-Fit constructs, and TAM. After all variables were entered into the model, CI was the strongest independent predictor of CPI ($\beta = 0.451$; $p < 0.001$), followed by PU ($\beta = 0.176$; $p = 0.031$), HL ($\beta = 0.168$; $p = 0.001$), and US ($\beta = 0.166$; $p = 0.043$). In contrast, TQ and OS no longer showed a significant relationship after being controlled for with other variables ($p = 0.063$ and $p = 0.051$). Of the sociodemographic characteristics, only education level remained independently associated with the CPI ($\beta = 0.152$; $p =$

0.011), while age, length of service, and occupation did not show a significant relationship. The Durbin–Watson value of 2.087 indicated no residual autocorrelation. Furthermore, the VIF value ranged from 1.270 to 6.392, and tolerance from approximately 0.156 to 0.787. These values indicate that multicollinearity was not extreme by common screening thresholds, but the upper VIF values and high pairwise correlations indicate meaningful shared variance.

Table 8. Multiple Linear Regression Analysis of Factors Associated with CPI (n = 60)

Variable	B	β	SE	t	p-value	95% CI	VIF	Tolerance
Age group	0.054	0.019	0.103	0.518	0.607	-0.154 to 0.262	1.270	0.787
Education level	0.254	0.152	0.100	2.540	0.011	0.058 to 0.450	3.184	0.314
Time as cadre	-0.003	-0.001	0.097	-0.035	0.972	-0.199 to 0.192	1.566	0.639
Occupation	0.098	0.021	0.172	0.573	0.570	-0.247 to 0.443	1.343	0.745
HL	0.169	0.168	0.050	3.405	0.001	0.069 to 0.269	2.322	0.431
TQ	0.203	0.137	0.107	1.901	0.063	-0.012 to 0.417	5.007	0.200
OS	0.219	0.163	0.109	1.999	0.051	-0.001 to 0.439	6.334	0.158
PU	0.213	0.176	0.096	2.223	0.031	0.021 to 0.406	6.037	0.166
US	0.230	0.166	0.111	2.082	0.043	0.008 to 0.452	6.125	0.163
CI	0.660	0.451	0.119	5.525	<0.001	0.420 to 0.900	6.392	0.156

Table 9. Summary of the Multiple Linear Regression Model (n = 60)

Statistic	Value
R	0.974
R^2	0.949
Adjusted R^2	0.938
F	90.946
p-value	<0.001
Durbin–Watson	2.087

These results show that, as compared to individual traits or opinions of the technology itself, CI to use is the most significant factor associated with CPI. These findings are consistent with the development of the Expectation Confirmation Model (ECM) and the TAM, which place desire to continue using technology as the main factor influencing continued use. When users have a strong desire to stick with an application, they are more likely to utilize it regularly, which improves task execution and program results (Han & Zo, 2023; Husnida et al., 2026; Lu et al., 2023). The importance of PU, HL, and US suggests that enhanced cadre performance is impacted not only by the desire to use the application but also by the cadre's comprehension of the technology, their belief that the application offers real advantages in their work, and a positive user experience. The HOT-Fit approach, which highlights that the fit between organizational, technical, and human elements is critical to the effective implementation of health information systems, is supported by these findings. Strong digital literacy will make it easier for people to use app features, and perceived usefulness and satisfaction will encourage continued use, which will ultimately improve performance (Husnida et al., 2026; Lu et al., 2023).

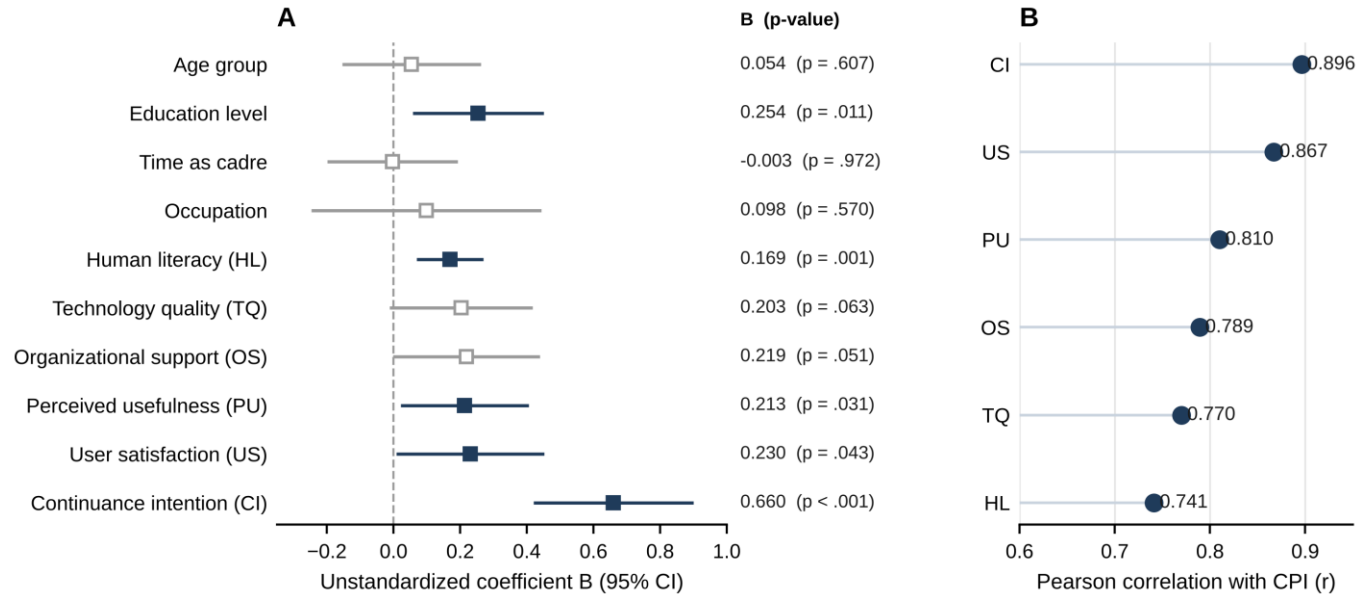


Figure 3. Factors associated with the Cadre Performance Index (CPI). (A) Unstandardized regression coefficients (B) with 95% confidence intervals from the multiple linear regression model; filled markers indicate p < 0.05. (B) Pearson correlation of each domain with CPI (n = 60)

It is interesting to note that, despite having a large correlation with CPI in the bivariate analysis, TQ and OS were no longer significant when other variables were taken into account. This implies that these two constructs probably have an indirect impact via raising PU, US, and particularly CI. To put it another way, if technology quality and organizational support don't increase users' perceptions of the app's utility, contentment, and commitment to stick with it in their daily practice, they won't be enough to boost performance. This pattern aligns with previous mHealth research demonstrating that adoption and sustained use are the main ways in which system quality influences performance (Han & Zo, 2023; Lu et al., 2023). Therefore, the development of applications should not be the primary emphasis of mHealth implementation; user capacity should also be strengthened through mentoring, training in digital literacy, and ongoing education, particularly for cadres with less education (Han & Zo, 2023; Husnida et al., 2026; Jeilani & Hussein, 2025). Overall, the study's findings show that organizational support and technology quality determine the effectiveness of mHealth implementation in enhancing cadre performance; however, these factors do not yield benefits as significant as improvements in perceived usefulness, user satisfaction, and the digital literacy of personnel when it comes to driving the intention for continued use and boosting cadre performance.

Practical and Policy Implications

The study's findings indicate that cadres' successful adoption of mHealth depends not only on user preparedness or technological excellence but also, and perhaps most importantly, on the application's sustained use. Therefore, sustaining application utilization within regular surveillance efforts must be the major goal of mHealth implementation techniques. Refresher training, regular supervision, feedback systems, and continuous technical support can all help achieve this. Additionally, to minimize discrepancies in application utilization, cadres with less education and experience need more rigorous mentoring. From a policy standpoint, these results highlight the necessity of integrating mHealth into the governance of DHF control programs through the establishment of sustainable monitoring and evaluation systems, the strengthening of organizational support, and the incorporation of the application into standard operating procedures (SOPs). Therefore, in order to improve the efficacy of community-based monitoring, digital transformation in healthcare must prioritize building user capacity and guaranteeing the application's continuous use in addition to technology provision.

Strengths and Study Limitations

This research has a number of advantages. To thoroughly assess mHealth deployment, it first combines the HOT-Fit model with the TAM. This clarifies the connections between technological, organizational, and human variables as well as user acceptance and community health worker performance. Second, by identifying continuance intention as the most important factor in raising the Cadre Performance Index (CPI), the study goes beyond a simple assessment of technology acceptance; this offers an empirical contribution to the understanding of mHealth implementation sustainability within community-based DHF surveillance programs. The study does have some drawbacks, though. There is a chance of response bias with convenience sampling and using self-reported surveys. The sample was small relative to the 10 predictors in the final regression model, and the sensitivity calculation limited power. In addition, the cross-sectional design does not allow causal inference or provide temporal evidence. Furthermore, it is important to exercise caution when extrapolating the findings to other regions because the study was only carried out in one. Thus, longitudinal or multicenter designs should be used in future studies to assess how mHealth usage behavior develops over time and improve the findings' external validity.

CONCLUSIONS

This study shows that the interaction of HL, PU, US, CI, and education level showed a statistically significant positive independent association with the CPI after adjustment, while TQ and OS did not. CI had the largest standardized independent association in the fitted model, but this should not be interpreted as evidence that CI causes higher cadre performance. The integrated HOT-Fit and TAM framework is useful for organizing the observed relationships, while future longitudinal and structural modelling is needed to examine temporal pathways, mediation, and generalizability.

SUGGESTION

The implementation of mHealth for DHF surveillance needs to prioritize sustaining app usage through periodic digital literacy training, mentoring, technical support, supervision, feedback, and integration of mHealth into routine dengue-surveillance workflows. Future research should involve larger sample sizes and broader geographic coverage, employ longitudinal designs to identify causal relationships, and utilize Structural Equation Modeling (SEM) to analyze the direct and indirect relationships among the HOT-Fit and TAM constructs and health worker performance.

ACKNOWLEDGMENTS

We would like to express our gratitude to the health cadres, cadre coordinators, and community health centers in Bungur, Senen, and Kemayoran (Central Jakarta), as well as Pulogadung (East Jakarta), Indonesia.

AUTHORS' CONTRIBUTIONS

All authors approved the final version of the manuscript and made substantial contributions to this study.

FUNDING

This study did not receive any specific grant from any funding agency.

COMPETING INTERESTS

The authors have declared no competing interests.

DECLARATION OF USING ARTIFICIAL INTELLIGENCE

The author used Grammarly for grammar correction and ChatGPT (OpenAI) for language editing, sentence structuring, and the visualization of the research flow diagram (Figure 1) and integration (Figure 3). After using these tools, the author thoroughly reviewed the manuscript, made necessary revisions, and assumes full responsibility for the content of the published article.

REFERENCES

Abdulaziz, S. G. (2021). *A theoretical framework for the adoption of cloud computing in hospital information systems*. University of Malaya (Malaysia). [Publisher]

Ahmetoglu, S., & Cob, Z. C. (2022). A systematic review of internet of things adoption in organizations : Taxonomy, benefits, challenges, and critical factors. *Applied Sciences, 12*(9), 4117. [Crossref], [Publisher]

Al-Jamili, O., Ibrahim, H., Ahmad, R., Ramayah, T., & Ghazali, O. (2026). Modeling user continuance usage intention of open government data (OGD): validation of an integrated model. *Journal of Enterprise Information Management*, *39*(1), 116–154. [Crossref], [Publisher]

Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2021). Factors Affecting the Adoption of Social Media in Higher Education: A Systematic Review of the Technology Acceptance Model BT - Recent Advances in Intelligent Systems and Smart Applications. In M. Al-Emran, K. Shaalan, & A. E. Hassanien (Eds.), *Recent Advances in Intelligent Systems and Smart Applications* (pp. 571–584). Springer International Publishing. [Crossref], [Publisher]

Alzghaibi, H. (2025a). Examining healthcare practitioners' perceptions of virtual physicians, mHealth applications, and barriers to adoption: Insights for improving patient care and digital health integration. *International Journal of General Medicine, 18*, 1865–1885. [Crossref], [Publisher]

Alzghaibi, H. (2025b). Healthcare practitioners' perceptions of mhealth application barriers: challenges to adoption and strategies for enhancing digital health integration. *Healthcare*, *13*(5), 494. [Crossref], [Publisher]

Asnadi, N. M., Durachman, Y., & Aripiyanto, S. (2025). Utilization of the hot-fit model to measure the success of information systems: A literature review. *2025 13th International Conference on Cyber and IT Service Management (CITSM)*, 1–6. [Crossref], [Publisher]

Bastan, M., Zarei, M., Tavakkoli-Moghaddam, R., & G., H. S. (2021). A new technology acceptance model: A mixed-method of grounded theory and system dynamics. *Kybernetes*, *51*(1), 1–30. [Crossref], [Publisher]

Byrne, A., & Nichol, B. (2020). A community-centred approach to global health security: implementation experience of community-based surveillance (CBS) for epidemic preparedness. *Global Security: Health, Science and Policy*, *5*(1), 71–84. [Crossref], [Publisher]

Castro, M. C., Wilson, M. E., & Bloom, D. E. (2017). Disease and economic burdens of dengue. *The Lancet Infectious Diseases*, *17*(3), e70–e78. [Crossref], [Publisher]

Cvetkovic-Vega, A., Maguiña, J. L., Soto, A., Lama-Valdivia, J., & Correa López, L. E. (2021). Cross-sectional studies. *Revista de la Facultad de Medicina Humana*, *21*(1), 164–170. [Publisher]

Dai, Q., Li, M., Yang, M., Shi, S., Wang, Z., Liao, J., Li, Z., E, W., Tao, L., & Tang, Y.-D. (2025). Attitudes, perceptions, and factors influencing the adoption of AI in health care among medical staff: nationwide cross-sectional survey study. *Journal of Medical Internet Research*, *27*, e75343. [Crossref], [Publisher]

Dehghani, R., & Kassiri, H. (2021). A review on epidemiology of dengue viral infection as an emerging disease. *Research Journal of Pharmacy and Technology*, *14*(4), 2296–2301. [Crossref], [Publisher]

Déniz García, A., Fabelo Gómez, H. A., Rodríguez Almeida, A. J., Zamora Zamorano, G., Castro Fernández, M., Alberiche Ruano, M. del P., Solvoll, T., Granja, C., Schopf, T. R., & Marrero Callicó, G. I. (2023). Quality, usability, and effectiveness of mHealth apps and the role of artificial intelligence: current scenario and challenges. *Journal of Medical Internet Research*. [Crossref], [Publisher]

Elepaño, A., Tan-Lim, C. S., Bankhead, C., Dans, L., Fabian, N. M., Sanchez, J., Dans, A., & Pope, C. (2026). Adoption of an electronic decision support tool for capacity building of community health workers: Mixed methods study. *JMIR Formative Research*, *10*, e69874. [Crossref], [Publisher]

Erku, D., Khatri, R., Endalamaw, A., Wolka, E., Nigatu, F., Zewdie, A., & Assefa, Y. (2023). Digital health interventions to improve access to and quality of primary health care services: a scoping review. *International Journal of Environmental Research and Public Health*, *20*(19), 6854. [Crossref], [Publisher]

Ghaith, A., Alshirbini, M., & Ma, H. (2026). Understanding surgeon adoption of artificial intelligence surgical technology: integrating UTAUT-TOE model. *Journal of Robotic Surgery*, *20*(1), 135. [Crossref], [Publisher]

Han, K., & Zo, H. (2023). Understanding the mobile healthcare applications continuance: The regulatory focus perspective. *International Journal of Medical Informatics*, *177*, 105161. [Crossref], [Publisher]

Husnida, N., Rahmatina, A. N., Wiwaha, G., Adnani, Q. E. S., & Hilmanto, D. (2026). Health cadre mentoring model in stunting prevention programs: A systematic literature review. *Journal of Multidisciplinary Healthcare*, 594400. [Crossref], [Publisher]

Ishengoma, F. (2024). Revisiting the TAM: adapting the model to advanced technologies and evolving user behaviours. *The Electronic Library*, *42*(6), 1055–1073. [Crossref], [Publisher]

Izah, S. C., Sylva, L., & Hait, M. (2023). Cronbach's alpha: A cornerstone in ensuring reliability and validity in environmental health assessment. *ES Energy and Environment*, *23*, 1057. [Crossref], [Publisher]

Jacob, C., Sánchez-Vázquez, A., & Ivory, C. (2020). Understanding clinicians' adoption of mobile health tools: a qualitative review of the most used frameworks. *JMIR MHealth and UHealth*, *8*(7), e18072. [Crossref], [Publisher]

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). Linear regression. In *An introduction to statistical learning: with applications in R* (2nd ed., pp. 59–128). Springer. [Crossref], [Publisher]

Jeilani, A., & Hussein, A. (2025). Impact of digital health technologies adoption on healthcare workers' performance and workload: perspective with DOI and TOE models. *BMC Health Services Research*, *25*(1), 271. [Crossref], [Publisher]

Kansiime, W. K., Atusingwize, E., Ndejjo, R., Balinda, E., Ntanda, M., Mugambe, R. K., & Musoke, D. (2024). Barriers and benefits of mHealth for community health workers in integrated community case management of childhood diseases in Banda Parish, Kampala, Uganda: a cross-sectional study. *BMC Primary Care*, *25*(1), 173. [Crossref], [Publisher]

Kılıç, B., & Durmaz, Y. (2026). Usability and behavioral intention in quasi-mandatory national digital health systems: The mediating role of e-satisfaction. *Journal of Nursing Management*, *2026*(1), 7864014. [Crossref], [Publisher]

Kolb, D. A. (2015). *Experiential learning: Experience as the source of learning and development* (2nd ed.). Pearson Education. [Google Scholar]

Lu, H.-H., Lin, W.-S., Raphael, C., & Wen, M.-J. (2023). A study investigating user adoption behavior and the continuance intention to use mobile health applications during the COVID-19 pandemic era: Evidence from the telemedicine applications utilized in Indonesia. *Asia Pacific Management Review*, *28*(1), 52–59. [Crossref], [Publisher]

Mazariego-Longoria, M., Rojas-Arbeláez, C., Vélez-Santamaría, H., Jiménez-Alejo, A., Dor, A., & Rúa-Uribe, G. (2026). Implementation fidelity of a community-based Aedes aegypti breeding site elimination program for dengue control in southeastern Mexico. *Plos One*, *21*(4), e0345163. [Crossref], [Publisher]

McGowan, C. R., Takahashi, E., Romig, L., Bertram, K., Kadir, A., Cummings, R., & Cardinal, L. J. (2022). Community-based surveillance of infectious diseases: a systematic review of drivers of success. *BMJ Global Health*, *7*(8). [Crossref], [Publisher]

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis* (6th ed.). John Wiley & Sons. [Publisher]

Mustafa, N. K., Ibrahim, R., Aizuddin, A. N., Aljunid, S. M., & Awang, Z. (2024). Critical success factors and acceptance of the casemix system implementation within the total hospital information system: Exploratory factor analysis of a pilot study. *JMIR Formative Research*, *8*, e56898. [Crossref], [Publisher]

Ng, N. E. L., & Kee, D. M. H. (2026). From adoption to retention: factors influencing continuance intention and the role of trust in digital health technologies. *Digital Transformation and Society*, *5*(3), 281–296. [Crossref], [Publisher]

Okafor, A. C., Imarhiagbe, O., & Ogwu, M. C. (2026). Dengue fever: Integrated approaches for sustainable disease management. In *Sustainable health practices for emerging tropical diseases* (pp. 53–86). Springer. [Crossref], [Publisher]

Omerovic, H. (2022). A literature review on vector-borne diseases. *International Journal of Medical Reviews and Case Reports*. [Crossref], [Publisher]

Or, C. K., Holden, R. J., & Valdez, R. S. (2022). Human factors engineering and user-centered design for mobile health technology: enhancing effectiveness, efficiency, and satisfaction. In *Human-Automation interaction: mobile computing* (pp. 97–118). Springer. [Crossref], [Publisher]

Pratama, N., & Lugito, H. (2017). Trends in dengue disease epidemiology. *Virology: Research and Treatment*, *2*. [Crossref], [Publisher]

Ramadhani, S. N. (2021). Impact of climate change on dengue hemorrhagic (DHF) in tropical countries. *Jurnal Kesehatan Lingkungan*, *13*(4), 219–226. [Crossref], [Publisher]

Rampinelli, V. P. C., Schmidt, C. R., de Oliveira, J. M. D., Celuppi, I. C., Mello, A. T., Hammes, J. F., Cunha, C. L., Wazlawick, R. S., Vieira, D. S. R., & Dalmarco, E. M. (2026). An evaluation framework for information systems from the users' perspective: a scoping review. *Journal of Health Informatics*, *18*, 1539. [Crossref], [Publisher]

Rasyid Ridha, M., Aisyah, S., Triana, Y., Priono, M., & Jumriadi, J. (2023). Improving community knowledge and behavior in the one house one jumantik program in dengue control. *Jurnal Kesehatan Masyarakat*. [Crossref], [Publisher]

Rivera, E. P., Arrivillaga, M. R., Juárez, J. G., De Urioste-Stone, S. M., Berganza, E., & Pennington, P. M. (2023). Adoption of community-based strategies for sustainable vector control and prevention. *BMC Public Health*, *23*(1), 1834. [Crossref], [Publisher]

Shah, S., Abbas, G., Riaz, N., ur Rehman, A., Hanif, M., & Rasool, M. F. (2020). Burden of communicable diseases and cost of illness: Asia-Pacific region. *Expert Review of Pharmacoeconomics & Outcomes Research*, *20*(4), 343–354. [Crossref], [Publisher]

Shin, D., Kim, J. S., Park, K., Pyo, M., Li, S. E., Kim, M., Lee, J., Oh, B. Y., Choi, Y., & Gerber, B. (2026). Experiences and acceptance of community-based mobile health services among people in underserved rural areas of Korea: Mixed methods study. *JMIR Formative Research*, *10*, e91368–e91368. [Crossref], [Publisher]

Sparidaens, E. M., Logger, J. G. M., Nelen, W. L. D. M., Braat, D. D. M., Fleischer, K., Hermens, R. P. M., & Sparidaens, E. M. (2023). Web-based guidance for assisted reproductive technology with an online app (myFertiCare): Quantitative evaluation with the HOT-fit framework. *JMIR Publications*, *25*, 1–12. [Crossref], [Publisher]

Sulistyawati, S., Surahma, S. A. M., & Sukesi, T. W. (2020). Understanding Community Involvement in Dengue Prevention in Sleman, Indonesia: A Free Listing Approach. *Journal of UOEH*, *42*(3), 231–236. [Crossref], [Publisher]

Tahir, F., Madandola, M. G., & Al-Ghamdi, S. G. (2023). Enhancing resilience: surveillance strategies for monitoring the spread of vector-borne diseases. *Sustainable Cities in a Changing Climate: Enhancing Urban Resilience*, 263–276. [Crossref], [Publisher]

Vandenbroucke, J. P., Von Elm, E., Altman, D. G., Gøtzsche, P. C., Mulrow, C. D., Pocock, S. J., Poole, C., Schlesselman, J. J., & Egger, M. (2021). Strengthening the reporting of observational studies in epidemiology (STROBE): explanation and elaboration. Translation to Russian. *Digital Diagnostics*, *2*(2), 119–169. [Crossref], [Publisher]

Veronika, S., Lee, M. S. W., Lang, B., & Putra, P. (2025). A systematic review and future agenda on continuance intentions in mobile apps. *International Journal of Information Management Data Insights*, *5*(2), 100352. [Crossref], [Publisher]

Wang, M., Huang, K., Li, X., Zhao, X., Downey, L., Hassounah, S., Liu, X., Jin, Y., & Ren, M. (2025). Health workers' adoption of digital health technology in low- and middle-income countries: a systematic review and meta-analysis. *Bulletin of the World Health Organization*, *103*(2), 126-135F. [Crossref], [Publisher]

WHO. (2023). *Dengue and severe dengue*. [Publisher]

Wijaya, M. C., & Kloping, Y. P. (2021). Validity and reliability testing of the Indonesian version of the eHealth Literacy Scale during the COVID-19 pandemic. *Health Informatics Journal*, *27*(1), 1460458220975466. [Crossref], [Publisher]

World Health Organization. (2022). *Monitoring the implementation of digital health: an overview of selected national and international methodologies*. [Publisher]

World Health Organization. (2023). *Data-driven policy-making and sharing of information on a common platform*. World Health Organization. Regional Office for South-East Asia. [Publisher]

Yusuf, F., Yulyanto, Y., & Priantama, R. (2026). A mixed-methods design for analyzing telemedicine adoption: An information systems approach integrating TAM–ISS, digital literacy, and usability. *Journal of Applied Data Sciences*, *7*(1), 303–325. [Crossref], [Publisher]

Zhai, Y., Yu, Z., Zhang, Q., Qin, W., Yang, C., & Zhang, Y. (2022). Transition to a new nursing information system embedded with clinical decision support: a mixed-method study using the HOT-fit framework. *BMC Medical Informatics and Decision Making*, *22*(1), 310. [Crossref], [Publisher]