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Understanding Consumer Acceptance of Portable Wi-Fi System Apps: An Integrated Model of Unified Theory of Acceptance and Use of Technology and Task-Technology Fit

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ABSTRACT

This study investigates consumer acceptance of a portable Wi-Fi system application in Indonesia by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-Technology Fit (TTF) models. Structural Equation Modeling (SEM) of data from 168 users was employed. The core findings reveal a significant theoretical deviation: the primary UTAUT constructs—Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI)—did not significantly affect behavioral intention. Task Characteristics (TAC) were also non-significant. Adoption was driven solely by Facilitating Conditions (FC). Within the integrated framework, Technology Characteristics (TEC) significantly influenced EE and TTF. The results conclude that for this utility-based application, acceptance hinges exclusively on foundational support infrastructure, not on performance perceptions, ease of use, or SI. This offers a critical theoretical refinement and a decisive practical focus for service providers and developers.

1. INTRODUCTION

Industry 4.0 is driving most industrial aspects to innovate and provide easier solutions through products or services. For example, communications service providers (CSPs) are now offering digital services and the Internet of Things, rather than just traditional communication services like voice and SMS [1]. Digital providers make it easier for society to access various things in this digital era [2]. To provide better service to customers, CSP is now developing a new product that allows people to enjoy internet connectivity anywhere, anytime, namely portable Wi-Fi. Portable Wi-Fi is a device that lets anyone connect to the internet easily and quickly.

Even though the technology behind smartphones and portable Wi-Fi is quite similar, portable Wi-Fi offers higher bandwidth and can be purchased through apps at a competitive price. This application system can be downloaded through the Google Play Store or App Store and provides diverse services, including modem settings, setup, website filtering, and mobile data purchasing. Despite the availability of the application system, User Adoption (UA) has been challenging. According to the CSP's annual report, the number of application users increased to 403,372 as of January 2022, but 35% of hard complaints were due to application service problems, often involving bugs and other issues. Customers frequently experience confusion when using the application system, which forces them to deal with customer service issues caused by top-up failures and mobile data activation. This creates a significant trust issue for CSP as an internet service provider. Thus, understanding the factors that impact user acceptance and adoption of this application system is crucial.

To proactively design interventions (such as training, socialization, etc.) targeted at user populations that may be less inclined to adopt and use the new system, managers can use the Unified Theory of Acceptance and Use of Technology (UTAUT) as a helpful tool to assess the likelihood of a successful introduction of a new technology and to better understand the drivers of acceptance [3]. UTAUT, as the extension of the Technological Acceptance Model (TAM), not only explores intentions towards technological advancement but also examines subsequent behavior [4].

Meanwhile, Task-Technology Fit (TTF) theory posits that information technology is more likely to enhance an individual's work performance when the IT's functionality aligns with the user's task requirements [5, 6]. The technology's capability to facilitate the task implies that its features enable efficient execution, lower costs, or simplified completion [7]. The qualities and knowledge of application users that influence the relationship between TTF and the use of information systems, as reflected in end-user satisfaction evaluation criteria, are commonly studied using TTF [8, 9].

UTAUT is the most comprehensive model for explaining technology acceptance, reflecting users' perceptions of technology, such as performance and effort expectations [10]. Meanwhile, TTF evaluates the fit between tasks and technology [5]. A conceptual model was employed to measure the relationships among variables to identify these factors, combining UTAUT and TTF. This combination of both approaches was chosen because it is thought to be able to explain how the system is evaluated from the viewpoint of the user, which includes the user's acceptance of the technology and the tasks that need to be completed, the expected performance, the expected ease of use, Social Influence (SI), and the state of the facilities to support the system's implementation. Thus, the research will identify the variables affecting the application's adoption, which will be used to improve and develop the application.

2. LITERATURE REVIEW

2.1 Unified Theory of Acceptance and Use of Technology and Task-Technology Fit model

Four primary elements impact the adoption and use of information technology by users: Performance Expectancy (PE), Effort Expectancy (EE), SI, and Facilitating Conditions (FC) [10, 11]. According to UTAUT, SI, PE, EE, and FC can all affect a technology's acceptability [12].

TTF consists of two exogenous variables, Technology Characteristics (TEC) and Task Characteristics (TAC), and one endogenous variable. The TTF model shows how compatibility between a task and a technology affects user acceptance of information systems such as internet services and cellular technology. TEC and TAC are two variables that influence TTF. TTF can show how compatibility between tasks and technology affects user acceptance of information systems, such as internet services and cellular technology. If a task exceeds the technology's capabilities or the technology lacks the necessary functions to complete it, compatibility between the task and the technology will decrease [13].

The UTAUT and TTF approaches are employed in this study to identify variables and indicators that can be improved to enhance service quality and address issues in the application. The UTAUT model focuses on user perceptions of technology, while TTF focuses on user acceptance from a TTF perspective. Technology adoption is not determined solely by users' perceptions of usefulness and ease of use, as emphasized in the UTAUT model, but also by the degree of fit between TEC and users' task requirements. Zhou et al. [10] demonstrate that TTF plays a critical role in shaping PE and EE, which are core constructs of UTAUT. When a technology aligns well with users' tasks, users are more likely to perceive it as valuable and easy to use, thereby increasing the likelihood of adoption. Conversely, even technologically advanced systems may fail to be adopted if they do not adequately support users' task needs. Integrating UTAUT and TTF, therefore, provides a more comprehensive framework by combining perceptual and functional perspectives. It has been shown to offer stronger explanatory power for technology adoption than either model used independently.

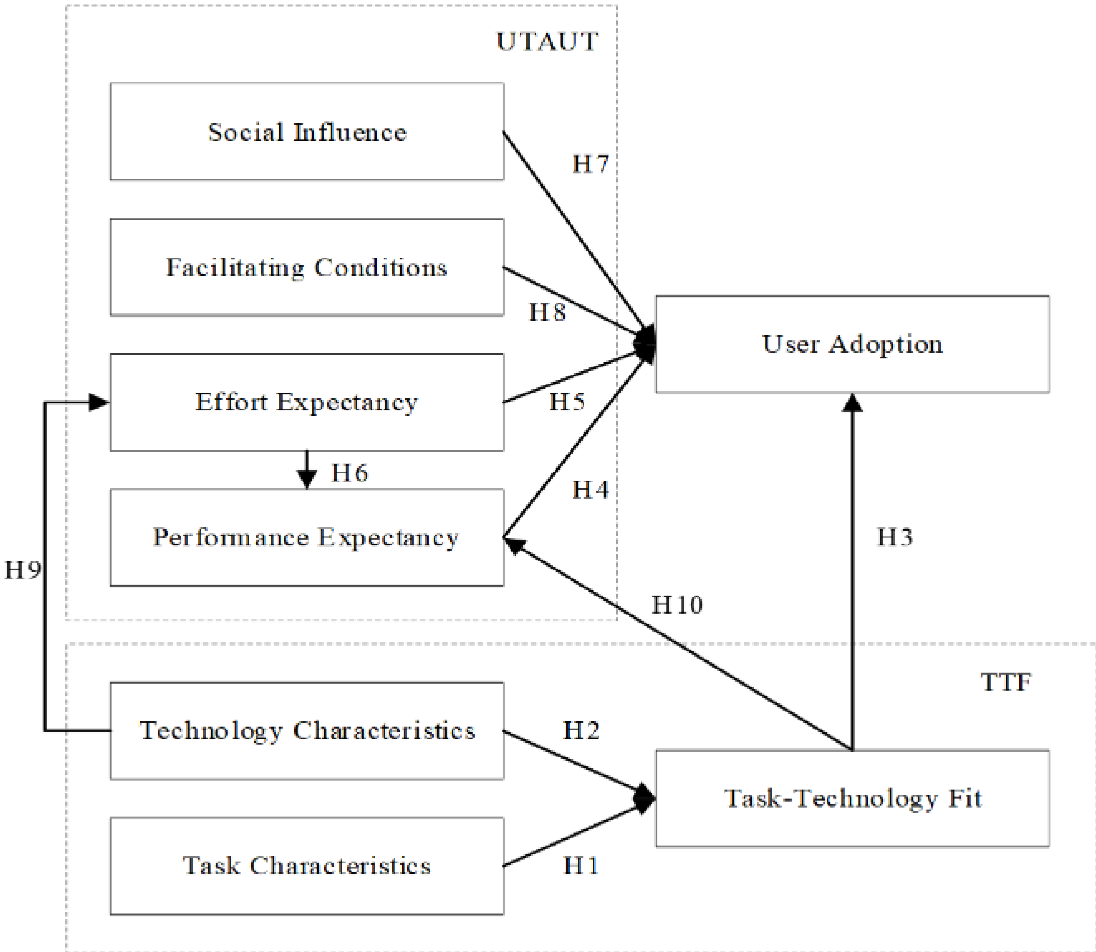

Figure 1. UTAUT and TTF conceptual model

Moreover, the UTAUT and TTF models have been applied in higher education, healthcare, and consumer contexts. In higher education, the UTAUT model has been widely used, focusing on technologies such as mobile learning tools and learning management systems. Studies indicate that PE is a significant predictor of behavioral intention [14-16]. However, the integration of TTF with UTAUT in educational settings remains underexplored, suggesting a gap in understanding how TTF influences technology acceptance in these contexts [17, 18].

On the other hand, in healthcare and consumer contexts, UTAUT2, an extension of UTAUT, has been applied, incorporating constructs such as hedonic motivation and price value [19, 20]. The integration of TTF in these contexts has shown that task characteristics and TEC significantly influence UA [21, 22].

2.2 Research model

In this study, an analytical model based on the model developed by Zhou et al. [10] was employed. The integration of the UTAUT and TTF models was deemed suitable for evaluating the acceptance of recent technology, considering existing problems. The variables used in this study are aligned with the research questions and are depicted comprehensively in Figure 1.

In this study, ten hypotheses were developed based on the conceptual model shown in Figure 1 to examine relationships among eight variables. The hypotheses are determined as follows. Compatibility between technology and tasks will drive UA. Conversely, incompatibility between technology and tasks will discourage UA [7, 23]. For instance, even though mobile banking is always accessible, users who do not require mobile transactions would opt for traditional banking services instead. Previous research has demonstrated the effect of TTF on the usage of the Knowledge Management System (KMS) [23]. Later studies also found that the interaction between tasks and technology affects users' blog use [24] and that the compatibility between tasks and technology affects users' use of information technology [25]. Based on these findings, this study proposes the following hypotheses: H1, H2, and H3.

The concept of PE is similar to perceived usefulness in the Technology Acceptance Model (TAM) and to relative advantage in the Innovation Diffusion Theory (IDT). It reflects users' perception that using a service system will improve their performance and make it faster and more effective. Previous studies have shown that PE affects UA and behavioral intention [26, 27]. Hence, the study proposes hypothesis H4.

EE refers to the user's perception of the ease of use of a service system and is equivalent to the perceived ease of use in the TAM/TAM2 model and complexity in the IDT model [11]. This factor represents how challenging it is for the user to operate the system. UTAUT posits that EE positively affects PE [11], meaning that when a user perceives a service system as effortless and straightforward to use, they have higher expectations for its performance. On the other hand, if a system is perceived as demanding or complicated, the user's performance expectations will be low. Previous studies have shown that EE can significantly impact UA in health information systems [28, 29]. This study, therefore, proposes hypotheses H5 and H6 to further explore this relationship.

SI is comparable to the subjective norm in the TRA model [11]. It refers to the impact of external factors, such as the opinions of friends, family, and superiors, on user behavior [30]. External factors can affect the adoption and utilization of a service system [31]. Previous studies on mobile banking have demonstrated the significant impact of SI on behavioral intention, including a study in Portugal [32]. Based on these findings, this study proposes hypothesis H7.

FC, in the TPB model, refer to perceived behavioral control and encompass the user's capabilities, knowledge, and resources [11]. Adoption and use of a new service system, such as portable Wi-Fi, requires specific skills, including setting up and using a mobile phone to connect to the modem and accessing financial resources. Users who lack the necessary operational skills or financial means may not adopt or use the system. For instance, the adoption rate of mobile payments increases when the operational infrastructure is in place and promotes its use [32]. Based on these findings, this study proposes hypothesis H8.

The TEC of the portable Wi-Fi system will impact EE. The application's benefits, such as ease of use and convenience, will simplify the setup process and reduce the time and effort required of users. Additionally, compared to traditional home internet, the portable Wi-Fi system has a more straightforward, more user-friendly interface, making it easier to use. These advantages will affect the user's perception of the effort required to use the system. The compatibility between the technology and tasks will also influence PE [25]. For instance, if a user's task requires fast, convenient, and accessible payments, they will view mobile banking as applicable and see an improvement in their performance. Conversely, they may adopt alternative technologies such as the internet or traditional banking services. Based on these findings, this study proposes hypotheses H9 and H10.

The hypotheses proposed in this study are as follows:

H1. TAC significantly influenced TTF.
H2. TAC of the portable Wi-Fi application service play a crucial role in determining the TTF.
H3. TTF significantly affects UA of portable Wi-Fi application services.
H4. PE significantly influences UA of the portable Wi-Fi application service.
H5. EE significantly influences UA of the portable Wi-Fi application service.
H6. EE significantly influences PE.
H7. SI significantly influences UA of the portable Wi-Fi application service.
H8. FC significantly influence UA of the portable Wi-Fi application service.
H9. TEC significantly influenced the user's EE.
H10. TTF significantly influences the user's PE.

3. METHODOLOGY

This study used survey methods, including online questionnaires, to collect primary data from a sample of customers who used portable Wi-Fi applications [33]. The sample was selected to accurately reflect various aspects of the population of portable Wi-Fi users [34]. The sample size for Structural Equation Modeling (SEM) analysis was determined by multiplying the number of indicators (26) by five, yielding a minimum sample size of 130 respondents [35]. This minimum sample size aligns with established standards, as studies have shown that a minimum sample size of 100 is suitable for analysis [36].

According to the research model in Figure 1, the research variables and their respective indicators were identified. Table 1 displays the variables and indicators utilized in this study.

Table 1. Variables dan indicators

Variable	Variable Code	Indicator	Code
User Adoption	USE	I frequently utilize the company's app service to manage my Wi-Fi devices.	USE1
		I extensively use the company's application services to top up my data quota.	USE2
		I often utilize company app services to monitor my data consumption.	USE3
Task-Technology Fit	TTF	I find the company's app service adequate for setting up my Wi-Fi.	TTF1
		I find the app service function from the company suitable for setting up my Wi-Fi.	TTF2
		The company's service functions satisfy my needs.	TTF3
Effort Expectancy	EE	Navigating the application services from the company is easy for me.	EE1
		I feel satisfied because the app service provided to be user-friendly.	EE2
		I found it easy to learn how to use the services offered by company apps.	EE3
		I find the interaction with the company's app service clear and easily understandable.	EE4
Performance Expectancy	PE	I find the services offered by the company to be extremely useful.	PE1
		The company's services make it easier for me to access the internet.	PE2
		The company's services enhance my comfort in using the internet.	PE3
		The company's service enables quicker access to the internet.	PE4
Social Influence	SI	The individuals who have an impact on my behavior encourage me to utilize the services provided by the company.	SI1
		People who are important to me think I should use the company's services.	SI2
		Reviews on social media influenced my decision to use the company's services.	SI3
Facilitating Conditions	FC	I have access to the necessary resources required to utilize the services offered by the company.	FC1
		I have the necessary knowledge to use the app.	FC2
		If I face any difficulties in using the app, experts will be available to assist me.	FC3
Technology Characteristics	TEC	The company's services are widely available.	TEC1
		The company provides real-time services.	TEC2
		The company provides safe and reliable services.	TEC3
Task Characteristics	TAC	I need to be able to manage my Wi-Fi devices at any time and place.	TAC1
		I need to be able to top up my quota at any time and location.	TAC2
		I require real-time access to device and account information anytime and anywhere.	TAC3

4. RESULT AND DISCUSSION

The questionnaire sample size was 168 participants. The demographics of the respondents, including age, gender, occupation, and usage duration, are summarized in Table 2. The data have been evaluated and confirmed as valid and reliable.

A path diagram of the overall model was constructed, including the variables and indicators for each. The path diagram is shown in Figure 2. The data used in the model were evaluated for validity and reliability, and it was determined that all latent variables were valid and reliable.

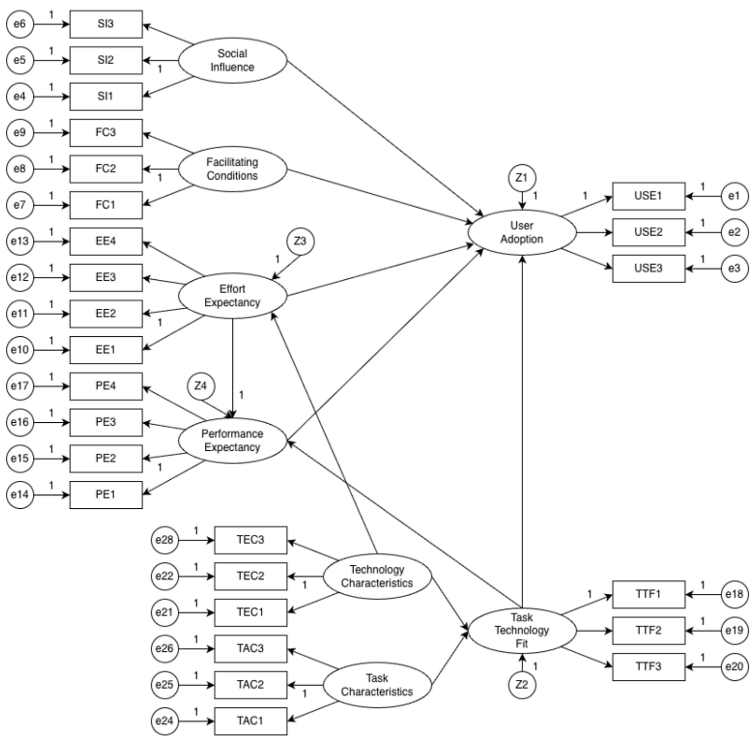

Figure 2. Path diagram

Table 2. Characteristic of respondents

Characteristic	Category	Total	Percentage
Age	19 – 26 years old	44	26.19%
	27 – 42 years old	86	51.19%
	43 – 57 years old	38	23.62%
Gender	Male	91	54.17%
	Female	77	45.83%
Profession	Student	22	13.10%
	Private sector	27	16.07%
	Government employee	23	13.69%
	Self-employed	34	20.24%
	Military/Police	15	8.93%
	BUMN employee	47	27.98%
Usage Duration	< 7 days	28	16.67%
	< 1 month	16	9.52%
	1 – 6 months	53	31.55%
	6 – 12 months	39	23.21%
	> 1 year	32	19.05%

The significance of the indicators in the model was evaluated, and any non-significant indicators were identified. The model data were assessed based on the loading factor. Table 3 shows that all indicators had loading factors greater than 0.5, indicating that the model can proceed to the next stage.

In the next phase, construct reliability (CR), average variance extracted (AVE), and discriminant validity tests were conducted, and the results are displayed in Table 4. All variables had CR values greater than 0.5, indicating high reliability of the constructs or indicators. If the AVE value is above 0.5, the indicators have a low error rate in representing the variable. Table 4 shows that only the SI variable has an AVE below 0.5, indicating a low correlation among its indicators. The indicators for the other variables show high correlation. The discriminant validity value for the exogenous variables was high, indicating that the constructs are distinct and effectively measure the variables. The discriminant validity of the exogenous variables was higher than the correlation factor loadings between them, demonstrating that the exogenous variables truly capture the phenomenon being measured.

Prior methodological studies [37, 38] suggest that convergent validity can still be acceptable when indicator loadings are significant, and CR values are close to or exceed 0.60, even if AVE is marginally below 0.50. In this study, most indicators exhibit acceptable and significant loadings, and the model is examined in a context-specific, exploratory setting where user tasks and perceptions are homogeneous, which may reduce measurement-level variance. Therefore, despite these limitations, the measurement model is considered adequate for interpreting the structural relationships.

Additionally, hypothesis testing was performed using the bootstrap technique with 500 bootstrap samples and a 95% Bias-Corrected Confidence Interval. The hypothesis is not rejected if the upper and lower bounds are of the same sign, either positive or negative, and the P value is less than 0.05 [39]. The hypotheses were evaluated using AMOS software and were as follows:

(1) H0: $\lambda 1 = 0$ (Significant influence)

(2) H1: $\lambda 1 \neq 0$ (Insignificant Influence)

The results of the hypothesis test using AMOS software are shown in Table 5.

According to Table 5, five hypotheses were rejected, H1, H3, H4, H5, and H10, because the upper and lower bounds were of different signs, and the resulting P value was more significant than 0.05 ($P > 0.05$). The processed data model is shown in Figure 3, where red lines indicate rejected hypotheses and blue lines indicate accepted hypotheses.

Table 3. Model data processing results

Dependent Variable		Independent Variable	Estimate
TTF	←	TEC	0.909
TTF	←	TAC	0.651
EE	←	TEC	1.308
PE	←	TTF	0.678
PE	←	EE	0.740
USE	←	TTF	0.992
USE	←	SI	1.496
USE	←	FC	1.025
USE	←	EE	0.925
USE	←	PE	1.723
USE1	←	USE	0.539
USE2	←	USE	0.508
USE3	←	USE	0.595
SI1	←	SI	0.610
SI2	←	SI	0.646
SI3	←	SI	0.569
FC1	←	FC	0.504
FC2	←	FC	0.524
FC3	←	FC	0.622
EE1	←	EE	0.596
EE2	←	EE	0.693
EE3	←	EE	0.583
EE4	←	EE	0.528
PE1	←	PE	0.662
PE2	←	PE	0.600
PE3	←	PE	0.503
PE4	←	PE	0.543
TTF1	←	TTF	0.635
TTF2	←	TTF	0.772
TTF3	←	TTF	0.641
TEC1	←	TEC	0.608
TEC2	←	TEC	0.573
TEC3	←	TEC	0.525
TAC1	←	TAC	0.543
TAC2	←	TAC	0.541
TAC3	←	TAC	0.507

Table 4. Reliability and average variance extracted tests

Variable	Discriminant Validity	Reliability Test	
		CR	AVE
USE	-	0.562	0.549
EE	-	0.693	0.632
PE	-	0.667	0.519
TTF	-	0.725	0.613
SI	0.609	0.638	0.371
FC	0.810	0.522	0.656
TEC	0.740	0.590	0.547
TAC	0.736	0.540	0.542

The model shows that the FC and SI variables influence UA. FC represent the user's perceived resources, while SI reflects the environmental impact on the use of service systems.

Based on the hypothesis-testing results in Figure 3, TEC significantly influence TTF, which, in turn, enhances research procedures but may not directly improve research performance

[40]. This suggests that while aligning technology with tasks can streamline processes, it does not always translate into improved performance outcomes. TAC also play a crucial role in determining TTF, emphasizing the importance of both the nature of the task and the technology used [40, 41].

EE, which refers to the ease of using technology, significantly affects PE and FC. This is consistent with findings that usability boosts user intentions and performance expectations [40-42]. EE has also been shown to positively affect behavioral intention, underscoring the importance of user-friendly technology in promoting adoption [40, 43, 44].

SI is a critical factor in technology adoption, affecting user behavior through peer and social norms [40, 45, 46]. This influence is decisive in environments where social interactions are prominent, such as social networks or collaborative settings [47, 48]. The role of SI varies with the observability of the technology and the adoption rate among peers, indicating that visible, widely adopted technologies are more likely to be adopted under social pressure [47, 49].

Table 5. Hypothesis test

Hypothesis	Structural Path	Std. β	SE	CR (T-Value)	P-Value	95% BCa CI	Conclusion
H1	TAC → TTF	−0.38	0.29	−1.37	0.170	[−0.941, 0.178]	Rejected
H2	TEC → TTF	0.71	0.32	2.27	0.023	[0.504, 1.458]	Accepted
H3	TTF → UA	0.12	0.13	0.90	0.367	[−1.671, 2.197]	Rejected
H4	EE → UA	0.41	0.25	1.65	0.098	[−0.309, 0.806]	Rejected
H5	PE → UA	0.29	0.26	1.08	0.277	[−16.391, 3.200]	Rejected
H6	TEC → EE	0.62	0.24	2.58	0.010	[1.216, 10.253]	Accepted
H7	TAC → EE	−0.54	0.26	−2.10	0.036	[−4.471, −0.174]	Accepted
H8	EE → PE	0.66	0.23	2.89	0.004	[0.457, 3.680]	Accepted
H9	SI → UA	0.59	0.21	2.77	0.006	[0.098, 0.680]	Accepted
H10	FC → UA	0.18	0.14	1.31	0.188	[−0.188, 0.966]	Rejected

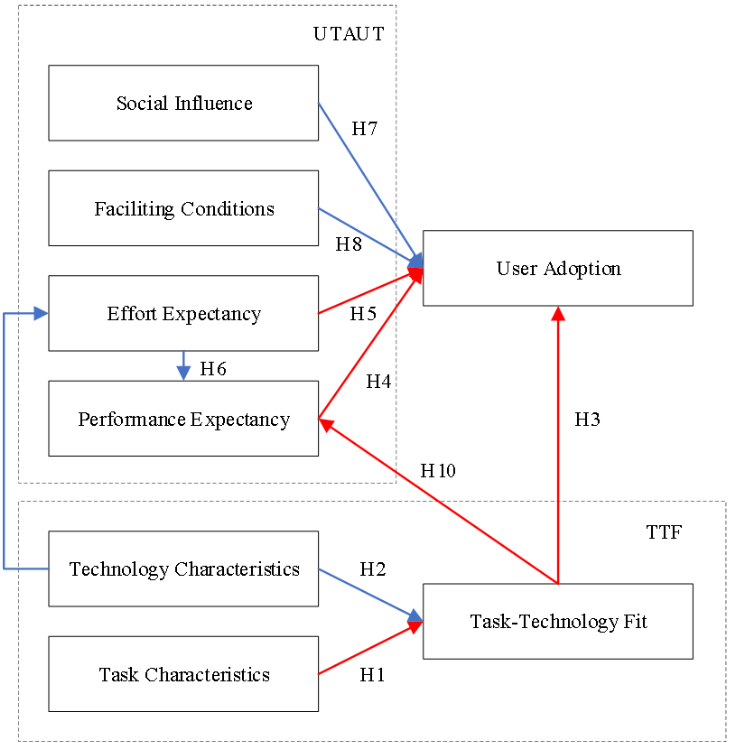

Figure 3. Model based on hypothesis testing results

In summary, TEC and TAC significantly influence TTF, which enhances research procedures but not necessarily performance [40, 41]. EE impacts PE and FC, emphasizing the role of usability in technology adoption [40, 42, 43]. SI plays a crucial role in user adoption, with its impact varying depending on observability and peers' adoption rates [47-49]. The integration of the UTAUT and TTF models offers a more holistic view of technology adoption, addressing both user perceptions and task alignment [22, 42, 50].

Despite support for hypothesized relationships, multiple paths were found to be insignificant in this study. H1 was not supported, indicating that TAC does not significantly influence TTF. This result suggests that users' tasks are homogeneous and routine, limiting the variability needed to shape perceptions of task–technology alignment. In such contexts, users tend to evaluate technology fit in a generalized manner rather than based on specific task differences. This finding contrasts with prior studies conducted in environments with more complex and diverse task structures.

H3 was rejected, indicating that PE does not significantly affect UA. This suggests that adoption is not driven by perceived performance improvement but rather by functional necessity. In the context of a utility-oriented and semi-mandatory application, users adopt the system to fulfill basic service needs rather than to enhance productivity. Consequently, performance-related perceptions become less influential in adoption decisions.

H4 was not supported, indicating that EE does not significantly influence UA. This result implies that ease of use is not a decisive factor, as users continue to use the application regardless of perceived simplicity. Given the standardized and familiar nature of digital interfaces, variations in perceived effort are minimal. As a result, EE does not play a critical role in adoption behavior.

H5 was rejected, suggesting that SI does not significantly affect UA. This indicates that adoption decisions are primarily individual and driven by personal or functional needs rather than social pressure or peer recommendations. The application's usage is primarily task-oriented rather than socially embedded. Therefore, SI becomes less relevant in this context.

H10 was not supported, indicating that TTF does not significantly influence PE. Although the technology may align with users' tasks, this alignment is perceived as a basic requirement rather than a source of performance enhancement. In routine and utility-based applications, TTF ensures usability but does not necessarily translate into perceived performance gains. Consequently, its effect on PE becomes insignificant.

After identifying the variables that influence the adoption of this portable Wi-Fi application, an analysis was performed on the current conditions associated with these variables. Previous research consistently shows that FC significantly affect UA across contexts, including infrastructure and resources, support systems, and ease of use. The availability of necessary infrastructure, such as internet access and mobile devices, is crucial for technology adoption. For instance, on online learning platforms, the availability of resources such as internet access and mobile devices significantly influences UA and persistence [51].

Moreover, adequate training and support systems are vital. In the context of AI-generated content design tools, FC were significant predictors of both behavioral intention and creativity outcomes [52]. Providing robust support systems can enhance UA and performance. FC also affect users' perceptions of ease of use and self-efficacy, which, in turn, shape their attitudes toward technology. For example, in educational settings, FC significantly influenced computer self-efficacy and perceived ease of use, which are critical for technology adoption [53].

Previous research also highlights various key points linking the variable SI to UA, including peer and social norms, technology anxiety, and cultural context. SI plays a significant role in shaping behavioral intentions. For example, in the adoption of healthcare devices, social impact has been found to significantly affect user attitudes and trust, which, in turn, influences behavioral intention [54].

Meanwhile, users with higher levels of technology anxiety rely more on SI when adopting recent technologies. This was evident in mobile shopping adoption, where users with high technology anxiety depended more on SI compared to those with low anxiety [55]. Social and cultural factors, including perceived credibility and exclusiveness, also influence technology adoption. In Ghana, SI and FC were significant predictors of mobile banking adoption [56].

Based on the linkage between the FC, SI, and UA, the practical recommendations are proposed. The company currently provides features related to the FC variable, including the service system server, Frequently Asked Questions (FAQ), and Customer Care features. However, these features still have shortcomings. Thus, it is recommended that robust infrastructure and support systems be ensured. Investing in high-quality servers will provide reliable and fast access to technology. This aligns with the importance of infrastructure in FC [51]. In addition, implement comprehensive support systems to help users navigate recent technologies, improving ease of use and self-efficacy [52, 53].

In accordance with the previous research, it is recommended to enhance and improve the performance of the service server by:

(1) Regularly inspecting the system for bugs that may affect service performance. If left unaddressed, these bugs can cause inconvenience for users, such as the display turning black during critical moments when the portable Wi-Fi application is needed.
(2) Creating a separate or backup server to manage multiple activities or tasks in the service system to avoid server overload. Implementing load balancing can also prevent server overload.

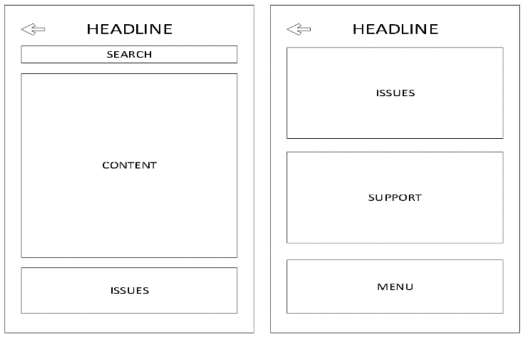

Figure 4. Wireframe display for new chatbot features and user interface

Other considerations for improving this application include incorporating chatbots and enhancing the user interface design to better assist users. Deploying chatbots will provide immediate assistance and support, address user queries, and reduce technology anxiety [55]. Use chatbots to streamline user interactions, making technology more accessible and user-friendly, which is crucial for adoption [51, 53]. After consulting with the company, creating a wireframe based on user evaluations, and incorporating best practices, a new chatbot feature and user interface design were developed, as depicted in Figure 4. Chatbot technology holds the potential to enhance service and boost customer engagement [57].

Furthermore, recommendations are provided based on the SI perspective regarding the company's current complaint-handling condition.

(1) Creating a guidebook on the conversational opening sequence with users, along with procedures for fostering good conversations to help solve their problems without escalating them to higher levels, will help shorten response times and reduce wait times for users.
(2) Implementing a monthly "product refresh meeting/class" to continually familiarize employees with the company's offerings, thus ensuring the prompt and proper handling of user inquiries.

Furthermore, partnering with influencers can shape positive perceptions and norms around recent technologies. Influencers can play a pivotal role in reducing technology anxiety and increasing trust [54, 55]. Ensure that influencer collaborations are also culturally relevant and credible to maximize their impact on UA [56].

Collaborating with influential figures, such as social media influencers or celebrities, through endorsement services or digital content creation can enhance marketing efforts and increase user acceptance and adoption of application service systems. This leverages the customers' tendency to be influenced by others, providing a wider reach and added benefits and security.

Recognizing that service systems play a crucial role in UA, this study has implications for service providers, technology developers, and policymakers. Firstly, service provider companies must thoroughly evaluate their current service systems, understand their functionality and limitations, and communicate these to both current and potential users. They must also promote the advantages and security offered by their innovative technology to increase user acceptance and adoption. To do this, they must assure users that their information is safe and secure and leverage social media to communicate the features of their service.

Secondly, the service system must be redesigned to improve the application interface and user involvement to encourage further adoption. The redesign should include adding new chatbot features and considering the internet infrastructure and connectivity. The interface should be improved to address users' different capacities and literacy levels, and the service system should be more responsive to user queries by hiring additional support staff or enhancing the system's capabilities to reduce the need for human intervention.

Thirdly, companies must proactively understand which technologies meet user needs and gradually integrate recent technologies while recognizing the drawbacks or limitations of existing technologies. They should invest in a service system with an attractive, responsive user interface that satisfies user expectations.

Finally, users will continue to adapt to new technological innovations and advancements. Thus, companies must be prepared to stay ahead of the curve by keeping abreast of user needs and updating their service systems accordingly.

4. CONCLUSIONS

The study found that the TTF model can be integrated with the UTAUT model. The TTF model examines how users affect the EE, PE, and UA of the service system. This study utilized 26 valid research indicators. The study's results indicated that the variables in the UTAUT and TTF models mutually influence one another. This relationship between variables showed that multiple variables affect the endogenous variables, as demonstrated by the bootstrap hypothesis-testing results. The findings from the data processing showed that the TEC variable affects TTF and EE; the EE variable affects PE and FC; and SI affects UA.

This study suggests multiple recommendations to the company to improve the FC, SI, and UA of their service system. Seven strategies are proposed to enhance the service system's effectiveness and usefulness, thereby increasing user acceptance and adoption of portable Wi-Fi applications. These strategies include maintaining and upgrading the company's service servers, enhancing the user interface, implementing a comprehensive complaint-handling program for customer support, improving the responsiveness of customer care, and conducting promotional and marketing campaigns in collaboration with influencers to boost customer adoption of portable Wi-Fi applications.

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