



An Engineering Perspective on School Digitalization Application Adoption in Indonesia: A Structural Model Using UTAUT2, TTF, and Trust

Andreas Wijaya*, Nilo Legowo

Mastter of Information Systems Management, Bina Nusantara University, Jl. Kebon Jeruk Raya 27, Jakarta, 11530, Indonesia

*andreasw96@binus.ac.id

Abstract. This study examines the factors that influence the acceptance of digital school applications in Indonesia against the backdrop of the gap between the number of registered users and active users. Data was obtained from 497 respondents and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The research model expands UTAUT2 by adding the variables Task-Technology Fit (TTF) and Trust. The results indicate that Trust significantly influences Usage Behavior ($\beta = 0.403$; $p < 0.001$), while Behavioral Intention is influenced by Social Influence ($\beta = 0.135$; $p = 0.016$), Facilitating Conditions ($\beta = 0.287$; $p < 0.001$), and TTF ($\beta = 0.292$; $p = 0.005$). Behavioral Intention further serves as the primary predictor of Use Behavior ($\beta = 0.495$; $p < 0.001$). The R^2 values of 0.788 for Behavioral Intention and 0.834 for Use Behavior indicate strong explanatory power. These findings emphasize the importance of building trust, infrastructure support, and technological suitability to enhance user engagement, while also providing practical insights for app developers and education policymakers.

Keywords: Adoption, Behavioral Intent, Digital Education, PLS-SEM, Task-Technology Fit, Trust, UTAUT2

(Received 2025-07-07, Revised 2026-04-27, Accepted 2026-04-27, Available Online by 2026-05-25)

1. Introduction

Nowadays, educational institutions in Indonesia are facing challenges in delivering a school digitalization solution while dealing with several factors like limited digital literacy among students and teachers, uneven infrastructure across Indonesia, especially in rural areas, and many more [1,2]. As

information and communication technology rapidly grows across all sectors, several companies realize this and start to develop a solution in this digital transformation era, which we now call education technology (edu-tech) services. While this digitalization solution offers many values like teaching and learning process and also access to previously not easily accessible knowledge, this also serves as a stimulant to students' adaptation process to technological advances in the future [3,4].

By blending computer hardware and software with educational theories, edu-tech aims to streamline and enhance the learning process. The rapid growth and widespread use of this technology are predicted, and Indonesia is likely to adopt it extensively. Edu-tech has proven to provide added value to educational institutions that use it, by providing more structured data, easier access to knowledge sources, and flexibility for users through the reduction of conventional processes that need to be carried out. One state-owned company has developed a school digitization application aimed at addressing various issues faced by rural schools, such as administration, student and teacher management, task distribution, assessment, effective school communication, and attendance tracking with minimal potential for fraud. The application is also designed adaptively according to the roles of users in the school, namely students, teachers, parents, and school administrators.

However, even though this app offers a bunch of benefits, the adoption rate in the field is still not consistent. The number of adoptions has increased significantly, but some obstacles still pop up, like low digital literacy among users, especially in rural areas, uneven digital infrastructure across Indonesia, and economic factors that limit access to electronic devices [5]. These challenges are in line with the global post-COVID-19 pandemic situation, where education around the world has experienced accelerated adoption of digital technology, but at the same time has revealed new gaps. In many low- and middle-income countries (LMICs), including Southeast Asia, issues of digital infrastructure, limited teacher training, and gaps in device access remain major obstacles. Recent studies in Southeast Asia indicate that the adoption of digital education in countries such as the Philippines, Vietnam, and Cambodia faces similar issues, including uneven internet connectivity, limited technical support, and digital skill gaps among educators [6–8].

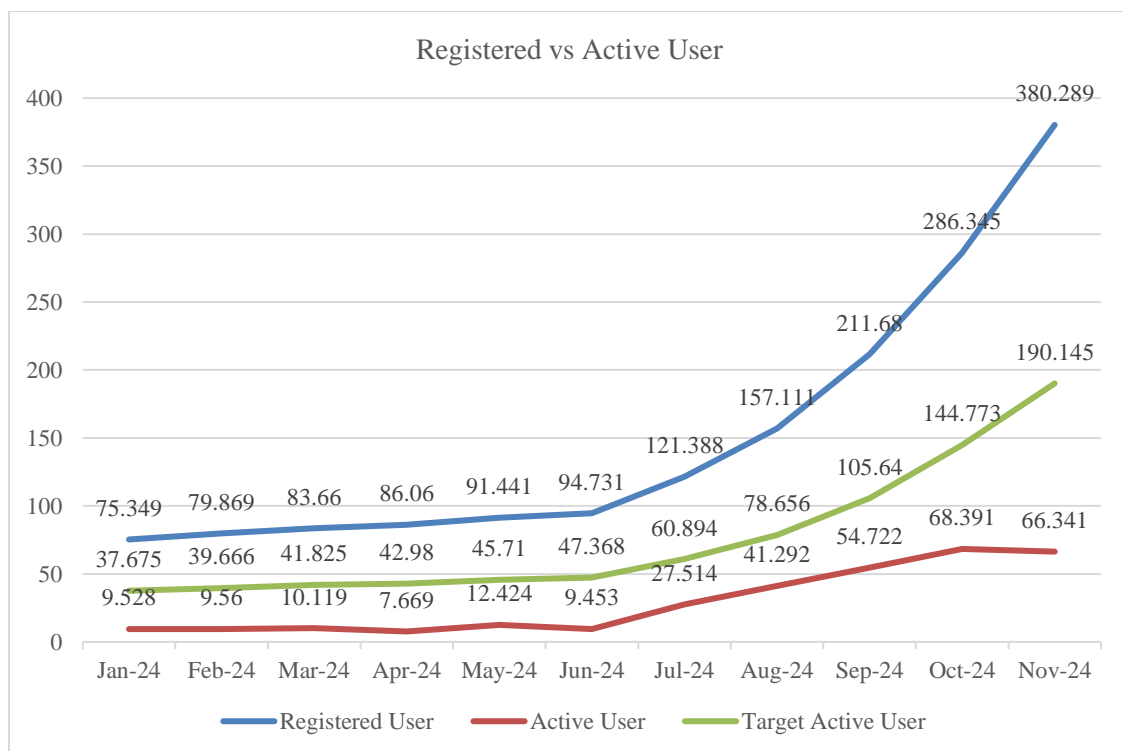


Figure 1. User Performance on State-Owned School Digitalization Application
02603014-02

The figure above shows the main reasons why this research is conducted. By getting the data source from the school digitalization application's perspective, we can see that while the number of adoption is increasing significantly, it is difficult to make this new adoption last, as the application's use retention is lacking, and they are more used to the conventional ways. Understanding the reason behind this lack of retention is crucial for making the strategic decision to fulfill the target and the application's full potential as a school digitalization application. This phenomenon highlights the need to understand the factors influencing sustained usage behavior, enabling developers and policymakers to design more effective strategies.

This study utilizes the UTAUT2 framework as the basis for analysis to understand the factors that influence the acceptance of applications. Choosing UTAUT2 was logical, given its widespread use and its track record for explaining the adoption of novel technologies [9]. According to this model, a person's decision to use technology and their actual usage are shaped by various factors, including the extent to which the technology is considered useful, how easy it is to use, social pressure or encouragement from those around them, the availability of infrastructure or resources, and the pleasure or satisfaction derived from using it. [10]. Although UTAUT2 has seven main variables, this study chose to exclude two of them, namely price value and habit. This decision was made because the application being studied does not require any costs, making the price aspect irrelevant for analysis. Habits were not taken into account because external factors, such as personal needs or recommendations from others, have a greater impact on how the application is used than individual habitual behavior. Thus, the research focus is directed toward factors more appropriate to the context of the application's use. To further convince this theory, according to Azizi et al. [11], a previous study shows that the UTAUT2 model is effective in identifying factors influencing technology adoption, even though Azizi et al's target research is more focused on medical education, in general, this still demonstrates the relevance in the educational context [12].

Apart from variables on UTAUT2, this study also incorporates perceived trust and task- technology fit. Trust, based on a previous study shown as a significant factor influencing technology adoption in education [13,14]. Also, according to Mohan's [14] Regarding "Massive Open Online Courses (MOOCs)," this study reinforces the findings by highlighting key factors driving the adoption of educational technology, such as internal or external motivations that prompt individuals to use technology, the level of simplicity and convenience when interacting with technology, and users' perceptions of the benefits and advantages gained. Besides these elements, Mohan places importance on "Goodhue and Thompson's task-technology fit (TTF) concept". This framework emphasizes that the success of technology use does not depend solely on motivation or ease of use, but also on how well the technology aligns with the needs and characteristics of the task it is intended to support [15]. This was further researched and proven by Almaiah et al. [16] and Zhou et al. [17], proving that when the technology used is truly suited to the type of task or user needs, it will increase a person's tendency to want to use it. Their study, which is relevant to our own, found that a significant match between available technology and the task to be done influences users' behavioral intention.

Based on these previous studies, although the UTAUT2 model is widely used to explain technology adoption, its application is still limited to the commercial or public service sectors and is rarely studied in depth in the digitization of public schools. Most research also only highlights the main constructs of UTAUT2 without integrating additional variables relevant to the world of education, such as Perceived Trust and Task-Technology Fit (TTF). In public education, factors like trust in data security and whether the technology is suitable for teachers' work are crucial for successful adoption. For this reason, the novelty of this research is in its unique combination of UTAUT2 with the concepts of Task-Technology Fit and Perceived Trust to explain how digitalization applications are adopted in public schools. This approach does not solely rely on the classical UTAUT2 constructs but also emphasizes the role of task-technology fit and user trust levels as key factors in shaping behavioral intentions and actual usage, thereby offering a distinct contribution from previous studies that have focused more on commercial-based education.

By empirically showing that the integration of UTAUT2, TTF, and trust can effectively explain technology adoption in formal education, this study makes a significant theoretical contribution to the existing literature. This study also shows that traditional factors such as performance expectations or hedonic motivation are not always dominant, but rather task-technology fit and trust are the keys to success. From a practical standpoint, the results of this research can help education policymakers and developers of school digitalization applications to create more effective adoption strategies. Emphasizing data security, transparency, and feature alignment with teachers' work needs will enhance sustainable use. Therefore, this study not only adds to the theory of technology adoption but also gives practical recommendations for putting digital transformation policies into action within Indonesian education.

By applying technology to all business activities, digital transformation brings about significant changes in how companies function and provide value to their customers. This not only changes analog data into digital format but also changes how we do things and how we work. Digital transformation is implemented differently across different business/aspects, but the main reason is to improve the process and result in comparison to doing things manually. Modern technology has revolutionized the way humans handle information and perform daily tasks. Artificial intelligence helps machines mimic human capabilities. Cloud computing provides access to flexible storage and computing resources without physical limitations. Meanwhile, the Internet of Things connects devices and systems in real-time, enabling data to be automatically collected from various sources and analyzed for more accurate decision-making. The combination of these technologies enables the automation of routine tasks, enhances productivity, and opens up opportunities for innovation that were previously hard to achieve [18,19].

Digital transformation is not just about using new technologies, but we also require cultural and structural changes so that we can utilize the full potential of this technology [20,21]. These cultural and structural changes mean there's a demand to develop new skills, changes in workflows, and how to communicate. For example, Edu-tech utilized digital transformation for electronic books (e-books), allowing students and teachers to access books without getting the books physically. The COVID-19 pandemic made digital transformation a critical and popular necessity. Furthermore, it significantly influences the global economy by fostering innovation, which in turn leads to economic growth. But bringing opportunities also presents challenges such as needing a deep knowledge of digital literacy, adequate resources, robust infrastructure, and many more. That said, countries, companies, or even people that can quickly adapt to this digital transformation will surely gain significant competitive advantages.

Venkatesh et al. [22] introduced the “Unified Theory of Acceptance and Use of Technology (UTAUT)” along with its extended version, UTAUT2. UTAUT is a theoretical model developed to understand the factors that influence the acceptance and use of technology. This model initially focused on organizations, emphasizing four main factors that influence the intention and behavior of technology use: “performance expectations, effort expectations, social influence, and supporting conditions.” The two dependent variables, namely “behavioral intention and usage behavior,” are used to measure the extent to which individuals or organizations intend to and actually use technology. Recognizing that individual behavior, especially that of consumer or educational technology users, has different characteristics from organizations, Venkatesh developed UTAUT2. This version adds three independent variables: “habit, hedonic motivation, and value”. It also uses moderating variables like age, gender, and experience to customize its predictions for different users. The effect of age is significant because biological changes that come with it like physical, cognitive, and sensory shifts can impact a person's skill in learning new technology. Consequently, older individuals often have less experience with technology, which hinders their adoption of it. Since they are accustomed to technology from a young age, younger people are often more comfortable with new technologies, which influences their adoption. Gender also plays a role, as men and women typically have different attitudes and preferences that can affect how they adopt technology. Past experiences with technology

influence how easily and quickly a person accepts new technology. Individuals who are accustomed to using various devices or applications tend to have higher digital competence, understand how technology works, and are able to overcome technical difficulties with greater confidence. In addition, previous experiences shape positive attitudes toward technology, making them more open and motivated to try new innovations. Conversely, less experienced users might need more support to master the technology, potentially reducing their motivation to use it in the long run. Both the original UTAUT and UTAUT2 frameworks have been widely used in diverse studies, such as those related to eLearning [19,23], eHealth [24,25], mobile banking [26], agriculture technology [27,28], automated vehicle adoption [29], ecommerce [30,31], social commerce [32–34].

2. Methods

2.1 Proposed Research Model and Hypotheses

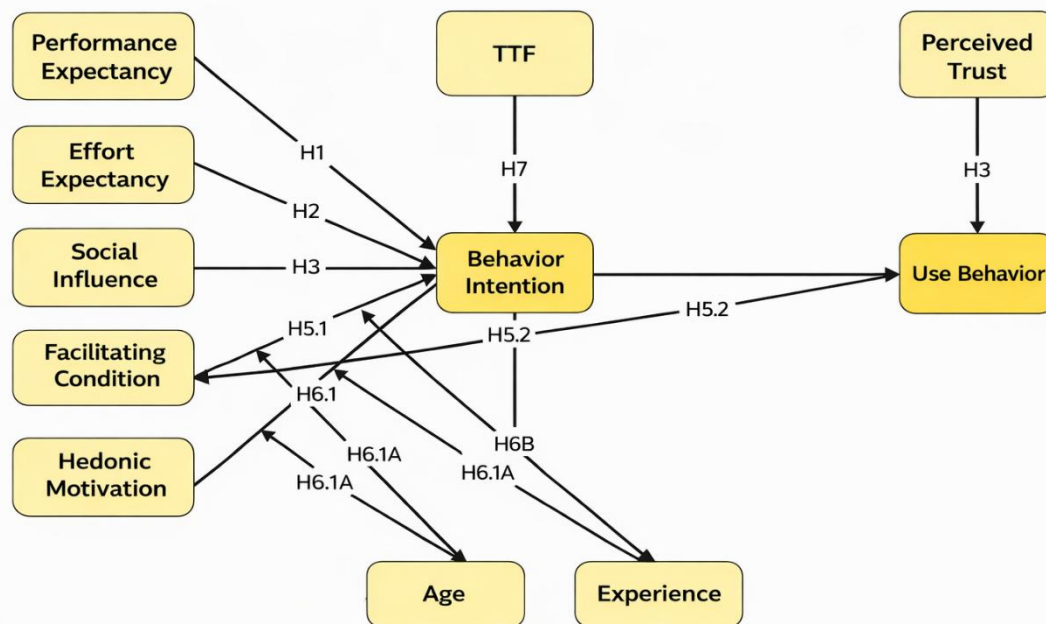


Figure 2. Proposed Research Model. Source: Author

The hypotheses in this study are formulated to examine the influence of several factors on Behavior Intention and Use Behavior. Performance Expectancy is hypothesized to have a significant influence on Behavior Intention (H1) [35], and Effort Expectancy is also expected to have a significant influence on Behavior Intention (H2) [36]. Furthermore, Perceived Trust is hypothesized to have a significant influence on Use Behavior (H3). Social Influence is also assumed to significantly influence Behavior Intention (H4). In addition, Facilitating Conditions are hypothesized to have a significant influence on Behavior Intention (H5.1) and Use Behavior (H5.2). The influence of Facilitating Conditions on Behavior Intention is further examined with moderating variables, namely Age (H5.1A) and Experience (H5.1B), which are assumed to strengthen the relationship. Moreover, Hedonic Motivation is hypothesized to have a significant influence on Behavior Intention (H6). This relationship is also moderated by Age (H6A) and Experience (H6B), which are expected to affect the strength of the relationship between Hedonic Motivation and Behavior Intention. Furthermore, Task Technology-Fit is hypothesized to have a significant influence on Behavior Intention (H7). Finally, Behavior Intention is expected to have a significant influence on Use Behavior (H8) [37].

2.2 Data Collection

This study used an online survey method to collect data from teachers who use school digitization applications. The number of respondents involved was 497, higher than the minimum requirement of 400 samples calculated using the Slovin formula with a margin of error of 5%, ensuring that the research results were more representative. The total population included 36,294 teachers registered in the application, providing broad coverage.

Sampling was conducted using probabilistic sampling with a proportional random approach, ensuring that each region was represented according to the number of app users in that area. The recruitment process was conducted formally through the application and school communications, ensuring transparency and formal involvement. Participation was voluntary, and respondents were required to provide written consent, demonstrating compliance with research ethics procedures. Additionally, this study was approved by the university's ethics committee, with assurances that respondents' identities would be kept confidential, thereby fulfilling privacy and personal data protection aspects.

2.3 Research Instruments

In this study, questionnaires were used as the main instrument to measure the variables under investigation. To maintain validity and reliability, the questionnaire items were adapted from previous relevant studies. Variables related to UTAUT2, namely “PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), FC (Facilitating Conditions), and HM (Hedonic Motivation)”, used scales from Venkatesh et al. [9,22]. Meanwhile, the scale for “PT (Perceived Task Fit)” was adapted from Almaiah et al. [14], and the “TTF (Task-Technology Fit)” scale was derived from Goodhue & Thompson [15] and Al-Rahmi et al. [12]. All items were adapted to fit the context of this study, namely the use of school digitalization applications. The questionnaire used a 5-point Likert scale, with 1 indicating strong disagreement and 5 indicating strong agreement. The instruments for this study were adapted to its unique requirements. To minimize Common Method Bias (CMB), this study implemented several procedural steps, such as concealing the purpose of the study from respondents, randomizing the order of items, and ensuring participant anonymity. In addition, statistical testing for CMB was conducted using Harman's single factor test and full collinearity VIF.

2.4 Analysis

After the questionnaire was distributed and the data successfully collected, the analysis was conducted using the PLS-SEM approach with the SmartPLS program. The analysis process consisted of two stages, namely measurement model testing and structural model testing [38].

At the measurement stage, construct validity and reliability are the focus. Convergent validity ensures that the indicators truly represent the construct, as indicated by $AVE > 0.50$. Construct reliability is examined using CA and $CR > 0.70$, which indicates good internal consistency. Discriminant validity ensures that each indicator is strong only on its target construct, tested through $HTMT < 0.85$ and cross-loadings.

The structural model stage assesses the relationships between constructs based on hypotheses. R^2 shows how much of the variance in the dependent variable is explained by the independent construct, while path coefficients assess the direction and strength of the relationship. To determine whether these relationships are statistically significant, bootstrapping with 5,000 subsamples is used, with a T-statistic > 1.964 or $P < 0.05$ as the significance threshold. With this approach, researchers can ensure that the model is not only valid and reliable but also provides empirical evidence for the relationships between the constructs being tested.

In addition, this study also conducted a moderation analysis to examine the role of age and experience variables. The moderation effect was evaluated by testing the significance of the interaction coefficient through a bootstrapping procedure. The moderation test's outcome, specifically a significant interaction path, indicated that the moderator had an impact on the power or direction of the relationship

between the independent and dependent variables. This test was preceded by a MICOM test, which was necessary to validate any group comparisons (for example, across different age or experience levels) and ensure they were free from measurement bias.

3. Results and Discussion

3.1 Research Instruments

Below is the research instruments used in this research, data was collected by Google Forms and In-App Notification that's also redirected to the form and compiled then analyzed using SmartPLS – PLS-SEM.

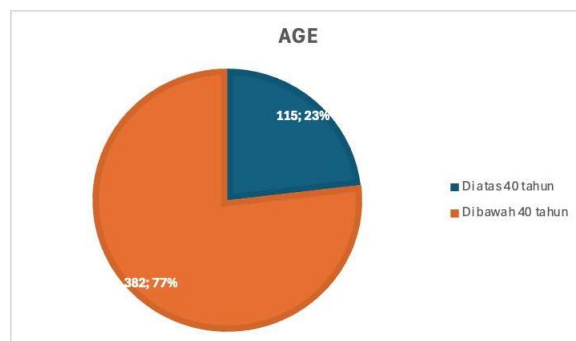
Table 1. Research Instruments

Variable	Items	Factors	References
<i>Performance Expectancy</i>	PE1	I believe that using the school digitalization application is beneficial for me.	[9,36]
	PE2	The school digitalization application helps me complete school-related activities more quickly.	[9,36]
	PE3	The school digitalization application makes my teaching and learning activities easier.	[9,36]
<i>Effort Expectancy</i>	EE1	The school's digitalization application is easy for me to use.	[9,37]
	EE2	The school's digitalization app is easy to get the hang of.	[9,37]
	EE3	I find the features in the school digitalization application easy to understand.	[9,37]
<i>Social Influence</i>	SI1	I use the school digitalization application because the people around me also use it.	[9,11]
	SI2	I use the school digitalization application because it is supported by important people around me.	[9,11]
	SI3	I was recommended to use school digitalization application by people whose opinions I value.	[9,11]
<i>Facilitating Conditions</i>	FC1	I'm confident in my ability to use the school's digitalization application.	[9,11]
	FC2	I am equipped with the necessary devices for the school's digitalization app.	[9,11]
	FC3	I receive assistance from the school digitalization application team if I encounter any difficulties.	[9,11]
<i>Hedonic Motivation</i>	HM1	I feel happy and satisfied after using the school digitalization application for teaching and learning activities.	[9,39]
	HM2	I find using the school digitalization application enjoyable.	[9,39]
	HM3	I find using the school digitalization application very entertaining for my daily teaching and learning activities.	[9,39]
<i>Task Technology-Fit</i>	TTF1	The school digitalization application is quite helpful in my teaching and learning activities.	[12]

	TTF2	The features in the school digitalization application are suitable for teaching and learning purposes.	[12]
	TTF3	I find that the school's digitalization application effectively supports my teaching and learning activities.	[12]
<i>Perceived Trust</i>	PT1	The school's digitalization application is a reliable tool for my teaching and learning process.	[12]
	PT2	Its security measures make the school digitalization application feel safe and reliable.	[12]
	PT3	I can entrust my personal data to school digitalization application.	[12]
	PT4	I feel assisted by the presence of the school digitalization application.	[12]
<i>Behavior Intention</i>	BI1	I foresee myself using the school's digital application going forward.	[9,16,40]
	BI2	I plan to use the school digitalization app on a daily basis.	[9,16,40]
	BI3	I plan to use the school digitalization application on a regular basis.	[9,16,40]
<i>Use Behavior</i>	UB1	I rely on the school's digitalization app for my daily teaching and learning activities.	[9,16,40]
	UB2	I prefer to use the school digitalization application rather than other applications.	[9,16,40]

3.2 Demographics

An online survey was carried out using a Google Form, and the target audience was everyone who is presently registered.



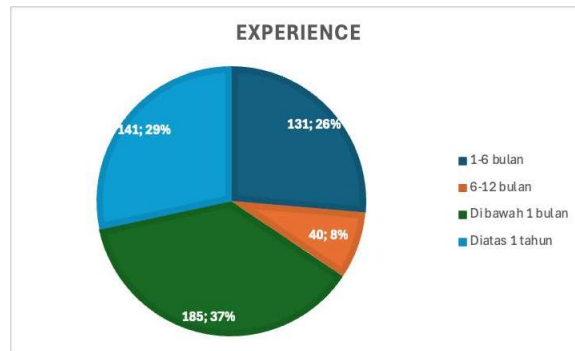


Figure 3: Demographics of Respondents

The data analysis sorted respondents by age and their history using the state-run school digitalization application, showing specific demographic and usage behaviors. While the exact number of respondents remains unspecified, the age distribution indicated that a significant majority, 77%, were under 40 years old, with the remaining 23% being over 40. This skewed distribution suggests that younger users generally reported higher comfort levels with technology.

In terms of experience with the application or similar platforms, the data revealed varied levels of familiarity. Specifically, 37% of the respondents had been using the application for less than one month, 26% had experience spanning 1 to 6 months, 8% had used the application for 6 to 12 months, and the remaining 29% had been using it for over a year.

3.3 Measurement Model Analysis

In PLS-SEM, the validity and reliability of the measurement model are very important. Convergent validity is examined through factor loadings ≥ 0.70 and AVE ≥ 0.50 , indicating that the indicators are consistent with the construct [39–41]. Discriminant validity is checked using cross-loadings to ensure that indicators are more closely related to their target constructs. Reliability is measured using Cronbach's Alpha and Composite Reliability, with values ≥ 0.70 considered good and ≥ 0.60 still acceptable [42,43]. With these criteria met, the measurement model is ready for structural testing.

Table 2. Validity & Reliability Test

Variable	Indicator	FL	AVE	CA	CR
Performance Expectancy	PE1	0.916	0.887	0.936	0.936
	PE2	0.956			
	PE3	0.954			
Effort Expectancy	EE1	0.943	0.906	0.948	0.948
	EE2	0.964			
	EE3	0.948			
Perceived Trust	PT1	0.916	0.844	0.938	0.939
	PT2	0.935			
	PT3	0.898			
	PT4	0.925			
Social Influence	SI1	0.871	0.808	0.881	0.886
	SI2	0.919			
	SI3	0.905			
Facilitating Condition	FC1	0.914	0.790	0.867	0.872
	FC2	0.881			
	FC3	0.871			

Hedonic Motivation	HM1	0.948	0.896	0.942	0.943
	HM2	0.946			
	HM3	0.946			
Task-Technology Fit	TTF1	0.961	0.917	0.954	0.955
	TTF2	0.950			
	TTF3	0.961			
Behavior Intention	BI1	0.953	0.915	0.953	0.953
	BI2	0.955			
	BI3	0.962			
Use Behavior	UB1	0.950	0.896	0.884	0.886
	UB2	0.943			

3.4 Structural Model Analysis

R² (R-Square) is used to assess the extent to which independent variables can explain the variability of dependent variables. The higher the R² value, the greater the model's ability to predict the outcome variable.

In this study, the model demonstrated strong predictive power, as the included variables explained 78.8% of the variance in Behavioral Intent, indicating that most individuals' intentions to use the application can be predicted by the analyzed factors. Additionally, these variables also explain 83.4% of the variance in Usage Behavior, indicating that actual app usage behavior is significantly influenced by the constructs tested in the model. This high R² value confirms that the study's structural model has good explanatory power and is relevant for understanding the factors influencing the acceptance and use of technology.

Table 3. R-Square

Variable	R-Square
Behavior Intention	0.788
Use Behavior	0.834

Path coefficients indicate the extent to which one construct influences another construct. Positive values indicate a direct relationship, while negative values indicate an inverse relationship. The magnitude of the path coefficient reflects the strength of the influence: the closer it is to 1 or -1, the more significant the influence of that construct on the target construct. Path coefficients are important because they not only indicate the presence of a relationship but also help assess the relative contribution of each predictor variable in the structural model, enabling researchers to understand which factors most determine the observed behavior or outcomes [44].

Table 4. Path Coefficient

	BI	UB	Remarks
PE	0.038		Positive
EE	0.046		Positive
PT		0.403	Positive
SI	0.135		Positive
FC	0.287	0.053	Positive
Age x FC	-0.085		Negative
Exp x FC	0.125		Positive
HM	0.162		Positive
Age x HM	0.067		Positive
Exp x HM	-0.090		Negative
TTF	0.292		Positive
BI		0.495	Positive

3.5 Hypothesis Measurement

To check if a relationship is significant by examining its T-statistic and P-value. For a 5% significance level, the T-value must be above 1.964 or the P-value must be below 0.05. The bootstrapping technique is frequently employed in this context to generate stable estimates of the model parameters, ensuring reliable inference regarding the significance of the paths within the model.

Table 5. Hypothesis Measurement

Hypothesis	Relationship	T-Statistics	P Values	Remarks
H1	PE -> BI	0.512	0.608	Rejected
H2	EE -> BI	0.656	0.512	Rejected
H3	PT -> UB	5.593	0.000	Accepted
H4	SI -> BI	2.400	0.016	Accepted
H5.1	FC -> BI	4.268	0.000	Accepted
H5.1A	Age x FC -> BI	1.707	0.088	Rejected
H5.1B	Exp x FC -> BI	2.302	0.021	Accepted
H5.2	FC -> UB	1.165	0.244	Rejected
H6A	HM -> BI	1.654	0.098	Rejected
H6B	Age x HM -> BI	1.292	0.197	Rejected
H6	Exp x HM -> BI	1.544	0.123	Rejected
H7	TTF -> BI	2.827	0.005	Accepted
H8	BI -> UB	7.466	0.000	Accepted

Based on Table 5, there are seven hypothesis rejected which three of them are incorporated with moderating variables, and six hypothesis is accepted, namely H3(PT>UB), H4(SI>BI), H5.1(FC>BI), H5.1B(Exp x FC>BI), H7(TTF>BI), H8(BI>UB)

3.6 Discussion

In earlier research by Boel et al. [37], Performance Expectancy showed a significant influence on Behavioral Intention, with a reported coefficient of 0.161. In contrast, the current study observes a non-significant effect of 0.038, indicating that this variable no longer drives intention to use school digitalization application as strongly as before. Users appear to have become accustomed to standard performance levels in digital applications, making perceived performance benefits less critical to their decision-making. Consequently, the hypothesis related to Performance Expectancy is rejected in the present context.

According to Rudhumbu et al. [39], Effort Expectancy exerted a significant influence on Behavioral Intention, demonstrated by a coefficient of 0.368 in their findings. In the current study, however, this factor yields a non-significant result 0.046. Such a discrepancy may be attributed to a population with high digital literacy and extensive experience using online platforms, where ease of use is now seen as a basic requirement rather than a distinguishing factor. As a result, the hypothesis regarding Effort Expectancy is also rejected in this research.

Findings related to Perceived Trust align with previous research by Almaiah et al. [16], which showed a significant effect on Use Behavior 0.180. In the current study this result aligns with the coefficient of 0.403 on Use Behavior. This suggests that trust is a crucial factor in increasing use behavior on the school digitalization application platform. This shows that if users feel that this application is trustworthy and has robust security over their personal information, they will be more motivated to use the school digitalization application. The increasing coefficient value shows that now the concern regarding trust and data privacy is increasingly highlighted so that this can be a major

consideration for developers and stakeholders to focus on improving this aspect.

The role of Social Influence in shaping Behavioral Intention remains pronounced, as evidenced by a coefficient of 0.135 in the current research. This aligns with Azizi et al. [11], who reported a coefficient of 0.241. The consistent significance of Social Influence highlights how recommendations from peers, educators, and other trusted community members can sway individuals' decisions to adopt school digitalization application. Given these statistically significant results, the hypothesis related to Social Influence is accepted.

Facilitating Conditions significantly affect Behavioral Intention with a coefficient of 0.287 in the current study, corroborating earlier findings by Azizi et al. [11], who noted a coefficient of 0.156. The presence of adequate infrastructure, technical support, and resources thus encourages users' intentions to utilize the school digitalization application platform. However, Facilitating Conditions did not exhibit a significant direct effect on Use Behavior 0.053, Hanelt et al. [18], who reported 0.053. While this factor promotes initial intention, it does not necessarily guarantee actual usage without the influence of other mediating elements. Overall, the hypothesis is partially supported accepted for its effect on Behavioral Intention but not on Use Behavior.

In contrast to Zacharis et al. [40], where Hedonic Motivation showed a coefficient of 0.131, the present study reports a non-significant effect of 0.162 on Behavioral Intention. This suggests that enjoyment or entertainment value is not a primary consideration for school digitalization application users. Instead, users place more emphasis on functional and practical features to support their educational tasks. Given the non-significant results, the hypothesis concerning Hedonic Motivation is rejected within this specific context.

Task-Technology Fit demonstrates a strong positive influence on Behavioral Intention, with a coefficient of 0.292, aligning well with Al-Rahmi et al. [12]. When school digitalization application effectively supports the tasks users need to accomplish, their intention to adopt and continue using the application increases. Proper alignment of the platform with user workflows and objectives not only enhances satisfaction but also promotes sustained engagement. The hypothesis related to Task-Technology Fit is therefore accepted.

Three out of four hypotheses involving age and experience as moderating variables are unsupported. The lack of significant moderating effects may be due to a relatively homogeneous user demographic characterized by high digital literacy. Consequently, variations in age and experience do not markedly alter the influence of the primary predictors (e.g. Trust, Social Influence, Task-Technology Fit) on Behavioral Intention and Use Behavior.

3.7 Implication

This study expands our knowledge of the drivers behind technology adoption in schools. The results indicate that perceived trust, social influence, facilitating conditions, and task-technology fit are important influences on the use of digital technology in an educational setting. This can be used as a reference or guideline for developers and stakeholders in the edu-tech sectors to improve the effectiveness of school digitalization applications.

The findings of this study highlight perceived trust as the most crucial element in the use behavior of the school digitalization application. Therefore, increasing trust in users must be the main focus of management. This can be done by making improvements to the data security side to make it more robust and transparent about the use of users' personal data. This will increase user confidence in using the application and increase user retention and loyalty.

Social influence also plays a significant part in encouraging a stronger behavioral intention in this study. This can also be a focus for management to improve. This can be done by holding a collaborative campaign targeting students, teachers and parents or by endorsing with educators and educational influencers who will directly increase motivation to use the application.

Facilitating Conditions also play an important role in this study. This shows that providing facilities and technical support is needed to increase technology adoption. From a managerial perspective,

improvements can be made in terms of responsive customer service, a qualified helpdesk system that is in accordance with the context of education and socialization of the application to schools. Quickly solving technical problems and giving clear instructions can lead to a direct increase in the intention to use the application.

A key finding of this study is that Task-Technology Fit has a considerable impact on Behavior Intention, indicating that the platform's features and user requirements must be closely aligned. Managers and developers should actively seek and incorporate user feedback, regularly evaluating whether the current system meets evolving educational needs. Continuous refinement of features such as lesson planning tools, progress tracking, and communication functionalities ensures that school digitalization application provides practical, relevant solutions. By tailoring the application to real-world classroom tasks, organizations can enhance user satisfaction and encourage more frequent, meaningful engagement.

4. **Conclusion**

This study confirms that Social Influence, Facilitating Conditions, and Task-Technology Fit are the main determinants of behavioral intention in using school digitalization applications, with Task-Technology Fit emerging as the most dominant factor. In addition, Perceived Trust is identified as the strongest predictor of actual usage, highlighting the importance of reliability, security, and transparency in encouraging sustainable technology adoption. These findings imply that developers and educational institutions should design systems that align closely with users' task needs while strengthening trust mechanisms. Academically, this study contributes to the literature on educational technology adoption by emphasizing the roles of task-technology fit and trust in school digitalization. However, the study has several limitations, including the use of a cross-sectional design that cannot capture behavioral changes over time, reliance on questionnaires that may introduce methodological bias, and a specific regional context that may limit generalizability. Therefore, future research is recommended to apply longitudinal approaches, experimental designs to test interventions that enhance trust, and data triangulation using actual usage logs, as well as to examine the model in other educational technology contexts or institutional levels for a more comprehensive understanding.

Declaration of AI and AI assisted technologies in the writing process

The authors utilized ChatGPT as an AI-assisted writing tool to support manuscript drafting, sentence restructuring, and language enhancement. All AI-generated suggestions were evaluated, modified, and validated by the authors prior to submission.

Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgements

This research was made possible by the continuous support and academic guidance from the management and academic team of the BINUS Graduate Program, Master of Information Systems Management at Bina Nusantara University. The authors are deeply grateful for their help. Special thanks are extended to all the respondents teachers from various educational institutions who voluntarily participated in the survey and provided valuable insights. Appreciation is also due to the development team of the State-Owned School Digitalization Application for their cooperation and assistance in data collection. The authors also want to thank the anonymous reviewers for their valuable feedback, which greatly improved the quality of this manuscript.

References

- [1] Singh RK, Singh A. Building sustainable digital education in India: transformation through equity, inclusion and accessibility. *SOSHUM: Jurnal Sosial Dan Humaniora* 2024;14:54–62.
- [2] Putra NP, Retnowardhani A. Unlocking User Satisfaction: A Delone & Mclean Is Success Model Approach To It Helpdesk Ticketing System Adoption. *Journal of Applied Engineering and Technological Science* 2024;6:610–25. <https://doi.org/10.37385/jaets.v6i1.4469>
- [3] Alenezi M. Deep Dive into Digital Transformation in Higher Education Institutions. *Education Sciences* 2021;11:770. <https://doi.org/10.3390/educsci11120770>
- [4] Arif M, Ismail A, Irfan S. AI-powered approaches for sustainable environmental education in the digital age: A study of Chongqing International Kindergarten. *International Journal of Environment, Engineering and Education* 2025;7:35–47
- [5] Rohayati Y, Abdillah A. Digital Transformation for Era Society 5.0 and Resilience: Urgent Issues from Indonesia. *Societies* 2024;14:266. <https://doi.org/10.3390/soc14120266>
- [6] Kunjiapu S, Sinnappan P, Salim FAA, Kunasegaran M. Challenges and dilemmas of digitalization in Philippine education: A grassroots perspective. *Journal of Public Administration and Governance* 2025;14:232.
- [7] Nhung NTH, Kien PT, Khanh MQ, Tinh TT, Phong TD. Digital Transformation in Vietnam's Education: Opportunities, Challenges, and Development Strategies. *Multidisciplinary Reviews* 2025;8:1–11. <https://doi.org/10.31893/multirev.2025282>
- [8] Sam R. Challenges and opportunities of educational technology integration in Cambodian higher education institutions: A literature review. Available at SSRN 4849873 2024:1–18. <https://doi.org/10.2139/ssrn.4849873>
- [9] Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS Quarterly* 2012;36:157–78.
- [10] Duan C. Advancing open education through open-source software: examining UTAUT 2 factors in adoption and implementation. *Asian Association of Open Universities Journal* 2024;19:313–26. <https://doi.org/10.1108/AAOUJ-09-2024-0119>
- [11] Azizi SM, Roozbahani N, Khatony A. Factors affecting the acceptance of blended learning in medical education: application of UTAUT2 model. *BMC Medical Education* 2020;20:367. <https://doi.org/10.1186/s12909-020-02302-2>
- [12] Al-Rahmi AM, Shamsuddin A, Wahab E, Al-Rahmi WM, Alturki U, Aldraiweesh A, et al. Integrating the Role of UTAUT and TTF Model to Evaluate Social Media Use for Teaching and Learning in Higher Education. *Frontiers in Public Health* 2022;Volume 10. <https://doi.org/https://doi.org/10.3389/fpubh.2022.905968>
- [13] Cunha MN, Chuchu T, Maziriri E. Threats, challenges, and opportunities for open universities and massive online open courses in the digital revolution. *International Journal of Emerging Technologies in Learning (IJET)* 2020;15:191–204
- [14] Mohan MM, Upadhyaya P, Pillai KR. Intention and barriers to use MOOCs: An investigation among the post graduate students in India. *Education and Information Technologies* 2020;25:5017–31. <https://doi.org/10.1007/s10639-020-10215-2>
- [15] Goodhue DL, Thompson RL. Task-technology fit and individual performance. *MIS Quarterly* 1995;19:213–36.
- [16] Almaiah MA, Alamri MM, Al-Rahmi W. Applying the UTAUT Model to Explain the Students' Acceptance of Mobile Learning System in Higher Education. *IEEE Access* 2019;7:174673–86. <https://doi.org/10.1109/ACCESS.2019.2957206>
- [17] Zhou T, Lu Y, Wang B. Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior* 2010;26:760–7. <https://doi.org/https://doi.org/10.1016/j.chb.2010.01.013>

- [18] Hanelt A, Bohnsack R, Marz D, Antunes Marante C. A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change. *Journal of Management Studies* 2021;58:1159–97. <https://doi.org/https://doi.org/10.1111/joms.12639>
- [19] Wessel LK, Baiyere A, Ologeanu-Taddei R, Cha J, Jensen TB. Unpacking the difference between digital transformation and IT-enabled organizational transformation. *Journal of the Association for Information Systems* 2021;22:102–29. <https://doi.org/10.17705/1jais.00655>
- [20] Aditya BR, Ferdiana R, Kusumawardani SS. Categories for barriers to digital transformation in higher education: An analysis based on literature. *International Journal of Information and Education Technology* 2021;11:658–64. <https://doi.org/10.18178/IJiet.2021.11.12.1578>
- [21] Rujira T, Nilsook P, Wannapiroon P. Synthesis of vocational education college transformation process toward high-performance digital organization. *International Journal of Information and Education Technology* 2020;10:832–7. <https://doi.org/10.18178/ijiet.2020.10.11.1466>
- [22] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view1. *MIS Quarterly* 2003;27:425–78.
- [23] Zhang X. A differentially private indoor localization scheme with fusion of WiFi and bluetooth fingerprints in edge computing. *Neural Computing and Applications* 2022;34:4111–32. <https://doi.org/10.1007/s00521-021-06815-9>
- [24] Lal V, Kumbhar V, Varaprasad G. Novel Extension of the UTAUT Model to Assess E-Learning Adoption in Higher Education Institutes: The Role of Study-Life Quality. *Knowledge Management & E-Learning* 2024;16:42–64. <https://doi.org/10.34105/j.kmel.2024.16.002>
- [25] Hassan IB, Murad MA, El-Shekeil I, Liu J. Extending the UTAUT2 Model with a Privacy Calculus Model to Enhance the Adoption of a Health Information Application in Malaysia. *Informatics* 2022;9:31. <https://doi.org/10.3390/informatics9020031>
- [26] Schretzlmaier P, Hecker A, Ammenwerth E. Extension of the Unified Theory of Acceptance and Use of Technology 2 model for predicting mHealth acceptance using diabetes as an example: a cross-sectional validation study. *BMJ Health & Care Informatics* 2022;29:e100640. <https://doi.org/10.1136/bmjhci-2022-100640>
- [27] Hilal A, Varela-Neira C. Understanding Consumer Adoption of Mobile Banking: Extending the UTAUT2 Model with Proactive Personality. *Sustainability* 2022;14:14708. <https://doi.org/10.3390/su142214708>
- [28] Oliveira T, Faria M, Thomas MA, Popovič A. Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management* 2014;34:689–703. <https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2014.06.004>
- [29] Siregar ZA, Anggoro S, Irianto HE, Purnaweni H. A systematic literature review: UTAUT model research for green farmer adoption. *International Journal on Advanced Science, Engineering and Information Technology* 2022;12:2485–90.
- [30] Dudás P V, Dávid LD. Unlocking the potential: UTAUT2 framework for embracing self-driving tractors in modern agriculture. *Journal of Infrastructure, Policy and Development* 2024;8:1–21. <https://doi.org/10.24294/jipd.v8i6.3442>
- [31] Ahmad S, Hwang D, Hwang Y. Factors affecting the adaptation of automated vehicles. *Human Technology* 2024;20:558–76.
- [32] Haryanti T, Pribadi A. Factors and theories for E-commerce adoption: A literature review. *International Journal of Electronic Commerce Studies* 2020;11.
- [33] Amofah DO, Chai J. Sustaining Consumer E-Commerce Adoption in Sub-Saharan Africa: Do Trust and Payment Method Matter? *Sustainability* 2022;14:8466. <https://doi.org/10.3390/su14148466>
- [34] Shoheib Z, Abu-Shanab EA. Adapting the UTAUT2 model for social commerce context. *International Journal of E-Business Research (IJEBR)* 2022;18:1–20. <https://doi.org/10.4018/IJEBR.293293>

- [35] Sonia PN, Hakim MM, Aryotejo G, Adhy S, Ashari YF, Alfarisi S. Factors Influencing the Use of Mobile Social Commerce Application with UTAUT2 Extended Model. *Journal of Information Systems Engineering & Business Intelligence* 2024;10.
- [36] Poureisa A, Aziz YA, Ng S-I. Swipe to Sustain: Exploring Consumer Behaviors in Organic Food Purchasing via Instagram Social Commerce. *Sustainability* 2024;16:2338. <https://doi.org/10.3390/su16062338>
- [37] Boel C, Rotsaert T, Valcke M, Rosseel Y, Struyf D, Schellens T. Are teachers ready to immerse? Acceptance of mobile immersive virtual reality in secondary education teachers. *Research in Learning Technology* 2023;31.
- [38] Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. *European Business Review* 2019;31:2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- [39] Rudhumbu N. Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal* 2022;17:15–36. <https://doi.org/10.1108/AAOUJ-08-2021-0084>
- [40] Zacharis G, Nikolopoulou K. Factors predicting University students' behavioral intention to use eLearning platforms in the post-pandemic normal: an UTAUT2 approach with 'Learning Value.' *Education and Information Technologies* 2022;27:12065–82. <https://doi.org/10.1007/s10639-022-11116-2>
- [41] Yildiz Durak H, Onan A. Predicting the use of chatbot systems in education: a comparative approach using PLS-SEM and machine learning algorithms. *Current Psychology* 2024;43:23656–74. <https://doi.org/10.1007/s12144-024-06072-8>
- [42] Mufidah I, Jiang BC, Lin S-C, Chin J, Rachmaniati YP, Persada SF. Understanding the Consumers' Behavior Intention in Using Green Ecolabel Product through Pro-Environmental Planned Behavior Model in Developing and Developed Regions: Lessons Learned from Taiwan and Indonesia. *Sustainability* 2018;10:1423. <https://doi.org/10.3390/su10051423>
- [43] Sarstedt M, Ringle CM, Hair JF. Partial Least Squares Structural Equation Modeling BT - Handbook of Market Research. In: Homburg C, Klarmann M, Vomberg A, editors., Cham: Springer International Publishing; 2022, p. 587–632. https://doi.org/10.1007/978-3-319-57413-4_15
- [44] Fauzi MA. Partial Least Square Structural Equation Modelling (PLS-SEM) in Knowledge Management Studies: Knowledge Sharing in Virtual Communities. *Knowledge Management & E-Learning* 2022;14:103–24.