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Evaluation of the Acceptance of the E-Catalog Application System for Construction Services Procurement in Government Using the UTAUT (Unified Theory of Acceptance and Use of Technology) Model

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Abstract

This study evaluates the acceptance of an e-catalog application system for construction service procurement in government using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The use of e-catalogs in procurement offers substantial benefits, including increased transparency, efficiency, and accountability. This research aims to identify factors influencing user acceptance of e-catalogs through an explanatory quantitative approach. This research uses an explanatory quantitative method, A sample of 100 respondents was selected using accidental sampling, and data were gathered through questionnaires, analyzed via Partial Least Square (PLS) to evaluate relationships between variables. Findings reveal that Effort Expectancy, Facilitating Conditions, and Habit significantly impact Use Behavior, while Behavioral Intention is influenced by Facilitating Conditions and Effort Expectancy. Meanwhile, Performance Expectancy, Social Influence, Hedonic Motivation, and Price Value show no significant impact on Behavioral Intention or Use Behavior. The conclusions indicate that ease of use and environmental support are key factors in promoting e-catalog usage.

Keywords: E-Catalog Application; Procurement; UTAUT

1 Introduction

The implementation of e-catalogs in the procurement of construction services within governmental settings offers numerous significant benefits (Firdaus et al., 2022). First, it greatly enhances transparency in the procurement process. E-catalogs make information on prices, specifications, and service providers openly accessible to all relevant parties, thereby reducing opportunities for corruption (Matsuda et al., 2021). Second, procurement efficiency improves as information is available in real-time and online, expediting the service provider selection process and lowering administrative costs, which are typically high with manual procedures (Anggraini Puspita Sari et al., 2024).

Furthermore, e-catalogs ensure the standardization of product and service quality, making it easier for the government to compare prices and quality from various providers (Hermawan, 2023). Accountability also improves as all transactions are well-documented, simplifying audits and tracking, while enabling better oversight by authorities (Elda et al., 2022). From a budgetary perspective, e-catalogs help the government secure more competitive prices and reduce budget waste through better standards and controls (Maharani et al., 2024). Finally, e-catalog implementation enhances service quality since registered providers undergo a stringent selection process, ensuring high responsiveness to procurement needs. Thus, e-catalogs not only streamline the procurement process but also boost accountability, efficiency, and transparency, which collectively contribute to more effective and efficient government budget utilization (Srimayasandy et al., 2024).

Despite the potential benefits, the adoption and utilization of e-catalog applications for construction services procurement in governmental settings remain low due to several major issues (Alfandi et al., 2023). Firstly, inadequate socialization and training leave many employees unfamiliar with this technology, leading them to

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prefer conventional methods (Irianto et al., 2023). Secondly, insufficient technological infrastructure, such as limited internet access, hampers the effective use of e-catalogs. Thirdly, resistance to change causes some stakeholders to feel more comfortable with traditional systems and reluctant to switch to e-catalogs. Fourthly, incomplete data integration reduces employees' confidence in the system (Fatchan et al., 2023). Fifthly, regulations and policies that do not fully support e-catalog implementation create confusion and uncertainty (Jannati et al., 2023). To address these challenges, there is a need for increased socialization and training, improvements in technological infrastructure, effective change management approaches, enhanced data integration, and regulatory and policy updates that support e-catalog adoption under the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Yohanes et al., 2020).

Testing the acceptance of e-catalog applications for construction services procurement in governmental settings using the UTAUT model is highly suitable, as this model encompasses key factors influencing technology adoption comprehensively (Angraini et al., 2024). UTAUT identifies four main factors—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—which are highly relevant in the context of e-catalogs. This model enables an in-depth analysis of how perceived benefits, ease of use, peer and supervisor influence, and infrastructural support affect the acceptance of this new technology (Yohanes et al., 2020). Moreover, UTAUT has proven effective in various technological and organizational contexts, providing a solid foundation for evaluating e-catalog acceptance (Dharma et al., 2023). This model also facilitates the analysis of usage differences based on demographic and organizational variables, helping to formulate appropriate implementation and training strategies to boost e-catalog adoption in government (Yohanes et al., 2020).

This research offers substantial novelty in evaluating the acceptance of e-catalog systems for construction services procurement in government settings using the UTAUT model. Empirically, this study not only evaluates standard factors like Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions but also incorporates additional variables relevant to the construction services procurement context, such as user satisfaction and system alignment with government regulations (Williams et al., 2015). Theoretically, this research expands UTAUT's application by adapting the model for the specific context of construction services procurement, enriching literature with insights on how this theory functions within a highly specialized and complex domain. Contextually, the study focuses on governmental environments with unique structures and regulations, providing deep insights into the challenges and opportunities encountered when adopting new technology in the public sector. The research method integrates quantitative and qualitative techniques, including surveys and in-depth interviews with government employees, to provide a comprehensive view of the factors affecting e-catalog adoption and identify training and support needs. Consequently, this study offers a new perspective on e-catalog evaluation and implementation, along with data-driven strategies to increase its acceptance in governmental settings (Yohanes et al., 2020).

The urgency of this research, titled "Evaluation of E-Catalog Application Acceptance for Construction Services Procurement in Government Settings Using the UTAUT Model," is high, as successful, transparent procurement plays a crucial role in optimizing government budget use and reducing corruption risks. Given the regulatory complexities in construction services procurement, it is essential to understand the factors affecting e-catalog acceptance, such as ease of use, infrastructural support, and social influence. This study not only helps identify and overcome e-catalog adoption barriers in government but also provides insights into how this technology can be tailored to meet the needs of the construction sector. Additionally, by applying the UTAUT model, this research contributes to both theoretical and practical understandings of technology acceptance in the public sector, offering data-driven strategies to enhance the effective implementation and utilization of e-catalogs.

This study aims to evaluate the acceptance of the e-catalog application system for construction services procurement in governmental settings using the UTAUT (Unified Theory of Acceptance and Use of Technology) model.

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2 Method

This study employs an explanatory quantitative research method. Explanatory quantitative research is conducted to investigate a population or sample, with results presented as numerical data that can reveal relationships or influences between the variables being studied.

2.1 Unified Theory of Acceptance and Use of Technology (UTAUT) Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical framework designed to help explain and predict user behavior related to technology adoption and use (Ndongfack, 2021). Developed by (Venkatesh et al., 2003; Alturise et al., 2022), and later expanded by Alturise et al. (2022), UTAUT integrates elements from eight leading technology acceptance models. The primary components of UTAUT include:

1. Performance Expectancy (PE): The individual's perception of how using the technology will enhance their job performance.
2. Effort Expectancy (EE): The degree of ease associated with technology use as perceived by the individual.
3. Social Influence (SI): The extent to which an individual feels that important others believe they should use the new technology.
4. Facilitating Conditions (FC): The individual's perception of the availability of technical infrastructure and organizational support for using the technology.
5. Hedonic Motivation (HM): The pleasure or satisfaction an individual feels from using the technology.
6. Price Value (PV): The individual's assessment of the trade-off between the cost of using the technology and the benefits gained from it.
7. Habit (HT): The extent to which an individual tends to perform an action automatically due to past consistent behavior.
8. Behavioral Intention (BI): The individual's intention to use the technology in the near future.
9. Use Behavior (UB): The actual use of the technology.

UTAUT2, an extension of the original UTAUT model, acknowledges the importance of factors such as hedonic motivation, price value, and habit in explaining the intention and use of technology, which were not present in the original UTAUT model (Bakarman & Almezeini, 2021).

2.2 Research framework

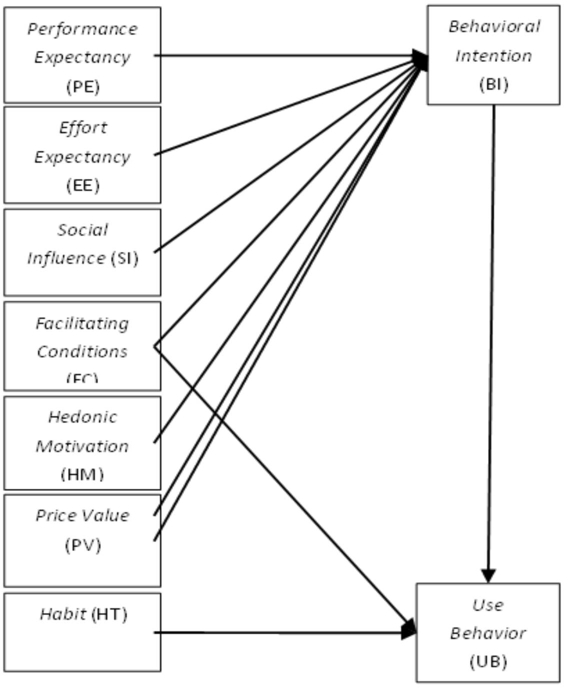

Figure 1. Research framework

The target population for this study consists of all construction services within the government sector. Given that the population size is large and not precisely known, the sample size is determined using Rao Purba's formula:

$$n = \frac{Z^2}{4 + (M_{oe})^2}$$

Description:

N = Sample size

Z = Confidence level for determining the sample, set at 95% = 1.96

M_{oe} = Margin of error, set at a maximum tolerable level of 10%

$$n = \frac{1{,}96^2}{4 + (0{,}10)^2}$$

$$n = 96{,}04$$

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According to this formula, the minimum sample size needed is 96.04, rounded up to 100 respondents. The researcher used an accidental sampling technique, aiming to select respondents that meet the study's criteria. The sample criteria include construction service providers who have used the e-catalog application.

The primary data for this study were gathered directly from respondents using questionnaires distributed through Google Forms. The questionnaire was designed using a scale to measure responses effectively.

Table 1. Rating scale

Statement	Score Value
Strongly Agree (SS)	5
Agree (S)	4
Neutral (N)	3
Disagree (TS)	2
Strongly Disagree (STS)	1

The data analysis in this study uses Partial Least Square (PLS), a structural equation modeling (SEM) approach based on variance, also known as component-based SEM. According to Hair et al., (2020), the goal of PLS-SEM is to develop or build theories (predictive orientation). PLS is used to explain the presence or absence of relationships between latent variables (predictions) and is a powerful method as it does not assume a certain scale of measurement and can handle small sample sizes.

2.3 Validity and Reliability Testing

Validity and reliability tests are conducted to ensure that the measurements used are accurate and reliable. The main tests include:

1. Convergent Validity: Assessed through the correlation between item/component scores and construct scores, with standardized factor loadings indicating the correlation strength between each measured item and its construct. For individual reflective measures, a high correlation is indicated by a score > 0.7.
2. Discriminant Validity: Measured by cross-loading indices between items and constructs. Discriminant validity is evaluated by comparing the root mean square of variance extracted (AVE); an instrument is considered valid if the AVE value > 0.5.
3. Composite Reliability: Assesses the reliability of a structure based on the coefficient of latent variables. A score > 0.70 indicates high construct reliability.
4. Cronbach's Alpha: A reliability test designed to confirm composite reliability results. A variable is considered reliable if Cronbach's alpha is > 0.7.

2.4 Instrument Testing

Table 2. Pengujian Instrumen

Uji Instrumen	Uji yang digunakan
Uji Validitas	Convergent Validity AVE
Uji Reliabilitas	Cronbach Alpha Composite Relibility

2.5 R-Square Testing

The R-square of the dependent construct is used to analyze the influence of specific independent variables on the latent dependent variable, showing the magnitude of the effect. A higher R-square value indicates a stronger influence of the independent variables on the dependent variable.

2.6 Inner Model

The inner model analysis, also known as the structural model, is a technique used to predict causal relationships between variables in the model. Hypotheses are tested during the inner model analysis using Smart PLS. In evaluating hypotheses, the t-statistic and probability values are observed:

- T-statistic: Used to test the hypothesis with a statistical threshold of 1.96 for a 5% alpha level.
- Beta Score: Shows the direction of the relationship between variables.

The criteria for accepting or rejecting a hypothesis are as follows:

- Alternative Hypothesis (Ha): Accepted if the t-statistic > 1.96 and p-values < 0.05, indicating a significant effect.
- Null Hypothesis (H0): Accepted if the t-statistic < 1.96 and p-values > 0.05, indicating no significant effect.

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3 Results and Discussion

3.1 Outer Model

Convergent Validity, Discriminant Validity, Composite Reliability, and Cronbach's Alpha are four criteria for outer model measurement used to evaluate the research's outer model. The following diagram provides a clearer illustration of the theoretical framework of this research:

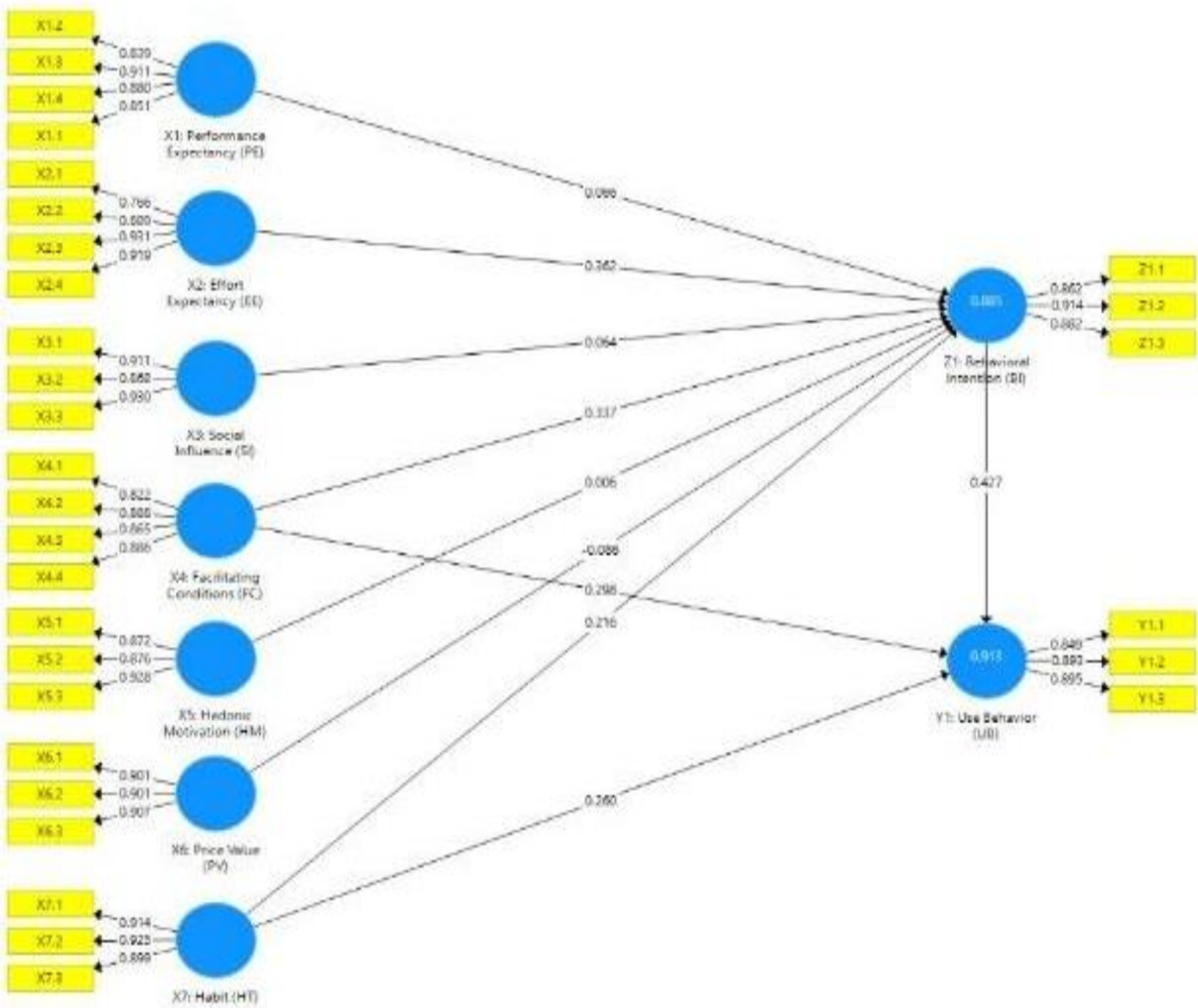

Figure 2. Outer Model
Source: Primary Data Processed (2024)

Based on the image above, it shows that the measurement results of outer loading on the reflective indicators reveal that most of the research indicators meet the criteria for use as measurement indicators for variables, as they have an outer loading value greater than 0.7 (outer loading > 0.7). Therefore, all indicators are considered eligible or valid for use in further research analysis.

3.2 Discriminant Validity

Each idea of a latent variable or construct must differ from each other latent variable or construct, and Discriminant Validity is used for this purpose. For the most updated reading, refer to the Heterotrait-Monotrait Ratio (HTMT). According to (Ghozali, 2018), a construct has strong discriminant validity if the HTMT value is below 0.90.

Table 3. Discriminant Validity

	PE	EE	SI	FC	HM	PV	HT	UB	BI
PE									
EE	0,983								
SI	0,978	1,035							
FC	0,992	1,042	1,033						
HM	1,011	1,061	1,011	1,084					
PV	0,941	0,959	1,030	1,054	1,008				
HT	1,029	1,013	1,027	1,008	1,020	0,984			
UB	1,036	1,081	1,038	1,055	1,065	0,988	1,041		
BI	0,992	1,048	1,017	1,043	1,042	0,969	1,021	1,088	

Source: Primary Data Processed (2024)

Based on the table, it can be seen that the HTMT ratio of all variables has an HTMT value less than 0.9 (HTMT < 0.9), so it can be said that all variable constructs have good discriminant validity.

Another method for measuring "discriminant validity" is by looking at the value of the "square root of average variance extracted" (AVE). The recommended value is above 0.5 (Ghozali, 2018). The AVE values generated in this study are shown in the following table:

Table 4. Average Variance Extracted

Variabel	Average Variance Extracted (AVE)
X1: Performance Expectancy (PE)	0,758
X2: Effort Expectancy (EE)	0,772
X3: Social Influence (SI)	0,816
X4: Facilitating Conditions (FC)	0,749
X5: Hedonic Motivation (HM)	0,796
X6: Price Value (PV)	0,815
X7: Habit (HT)	0,833
Y1: Use Behavior (UB)	0,773
Z1: Behavioral Intention (BI)	0,786

Source: Primary Data Processed (2024)

Based on the table above, it is known that all research variables have met the AVE standard value above 0.5 (AVE > 0.5). The Performance Expectancy variable has an AVE value of 0.758, the Effort Expectancy variable has an AVE value of 0.772, the Social Influence variable has an AVE value of 0.816, the Facilitating Conditions variable has an AVE value of 0.749, the Hedonic Motivation variable has an AVE value of 0.796, the Price Value variable has an AVE value of 0.815, the Habit variable has an AVE value of 0.833, the Use Behavior variable has an AVE value of 0.773, and the Behavioral Intention variable has an AVE value of 0.786. The AVE value of each variable was calculated, and it can be concluded that all variables with an AVE value higher than 0.5 meet the discriminant validity threshold. Thus, each variable has strong discriminant validity.

3.3 Composite Reliability

The composite reliability of the indicator blocks for each construct is the next aspect to be evaluated. According to (Ghozali, 2018), a construct is considered reliable if its composite reliability value is greater than 0.70. The outer model findings that illustrate the composite reliability of each construct are as follows:

Table 5. Composite Reliability

Variabel	Composite Reliability

X1: Performance Expectancy (PE)	0,926
X2: Effort Expectancy (EE)	0,931
X3: Social Influence (SI)	0,930
X4: Facilitating Conditions (FC)	0,923
X5: Hedonic Motivation (HM)	0,921
X6: Price Value (PV)	0,930
X7: Habit (HT)	0,937
Y1: Use Behavior (UB)	0,911
Z1: Behavioral Intention (BI)	0,917

Source: Primary Data Processed (2024)

The table above shows satisfying composite reliability results, where the Performance Expectancy variable has a composite reliability value of 0.926, the Effort Expectancy variable has a composite reliability value of 0.931, the Social Influence variable has a composite reliability value of 0.930, the Facilitating Conditions variable has a composite reliability value of 0.923, the Hedonic Motivation variable has a composite reliability value of 0.921, the Price Value variable has a composite reliability value of 0.930, the Habit variable has a composite reliability value of 0.937, the Use Behavior variable has a composite reliability value of 0.911, and the Behavioral Intention variable has a composite reliability value of 0.917. These results show that the composite reliability values for all variables are greater than 0.7, indicating that the research variables have high reliability.

Cronbachs Alpha

Cronbach’s alpha can be used to provide weight to the composite reliability test mentioned above. If the Cronbach’s alpha for a particular variable is greater than 0.7, the variable can be considered reliable (Ghozali, 2018). The Cronbach’s alpha for each variable is presented below.

Table 6. Cronbachs Alpha

Variabel	**Cronbach's Alpha**
X1: Performance Expectancy (PE)	0,894
X2: Effort Expectancy (EE)	0,899
X3: Social Influence (SI)	0,887
X4: Facilitating Conditions (FC)	0,888
X5: Hedonic Motivation (HM)	0,872
X6: Price Value (PV)	0,887
X7: Habit (HT)	0,900
Y1: Use Behavior (UB)	0,853
Z1: Behavioral Intention (BI)	0,863

Source: Primary Data Processed (2024)

Based on the data shown above in Table 4, it can be confirmed that the Cronbach’s alpha value for each research variable is > 0.7. Thus, it can be concluded that the reliability of all research variables is good, as each variable has a Cronbach’s alpha value above 0.80.

3.4 Inner Model

Path Coefficient Test

The path coefficient reveals the relative significance of the association between constructs. The t-test (critical ratio) obtained through the bootstrapping procedure (resampling method) can be used to evaluate the significance of the path coefficient, provided that the sign is consistent with the hypothesized theory. The results of the t-test between the inner and outer models are as follows:

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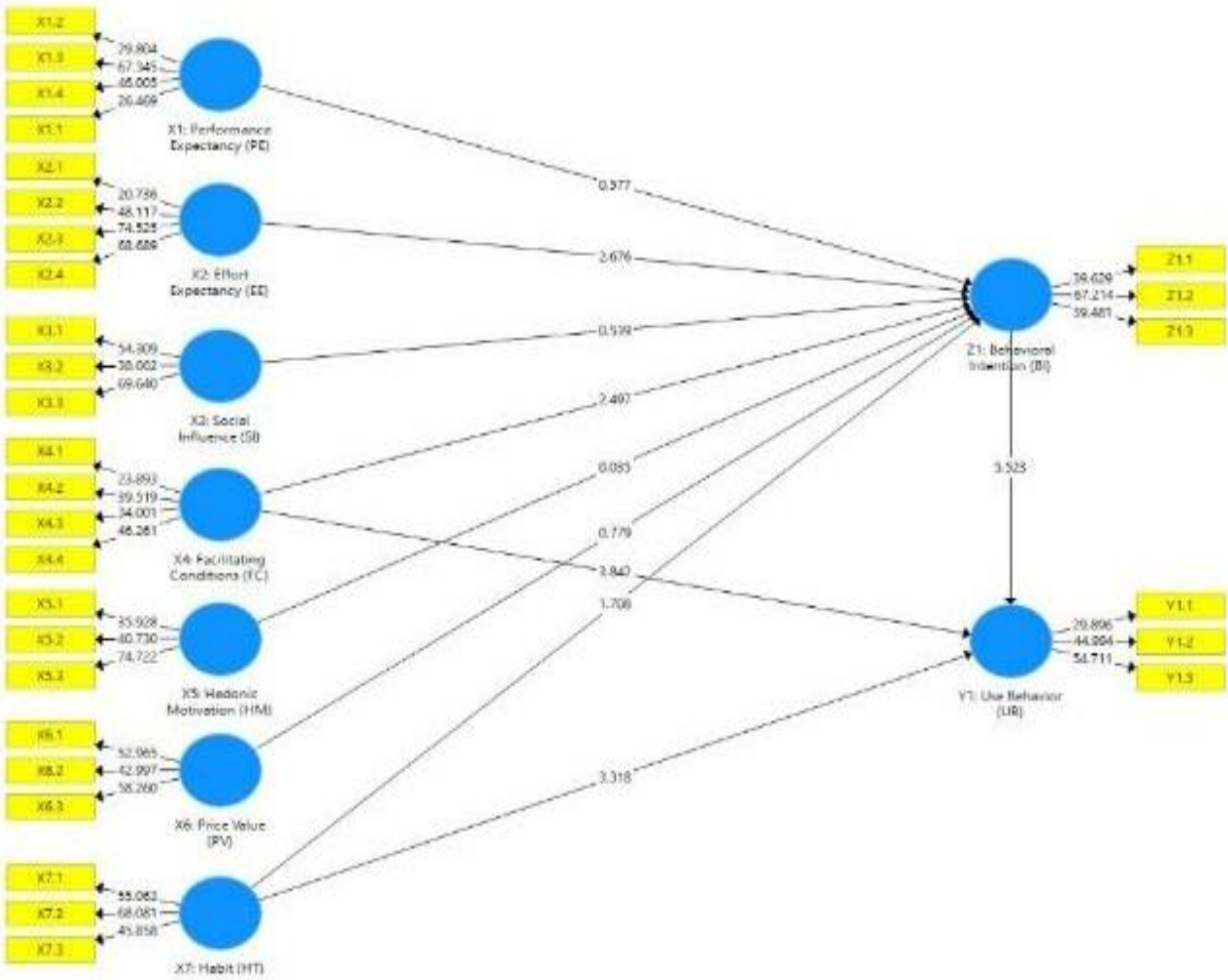

Figure 3. Inner Model
Source: Primary Data Processed (2024)

The t-test used here is derived from the bootstrap sample. We will next compare the t-table values with the results of the t-test depicted in the above image.

Table 7. Hypothesis testing results

	T Statistics	P Values
X1: Performance Expectancy (PE) -> Y1: Use Behavior (UB)	0,551	0,582
X1: Performance Expectancy (PE) -> Z1: Behavioral Intention (BI)	0,577	0,564
X2: Effort Expectancy (EE) -> Y1: Use Behavior (UB)	2,092	0,037
X2: Effort Expectancy (EE) -> Z1: Behavioral Intention (BI)	2,676	0,008
X3: Social Influence (SI) -> Y1: Use Behavior (UB)	0,552	0,581
X3: Social Influence (SI) -> Z1: Behavioral Intention (BI)	0,539	0,590
X4: Facilitating Conditions (FC) -> Y1: Use Behavior (UB)	4,834	0,000
X4: Facilitating Conditions (FC) -> Z1: Behavioral Intention (BI)	2,497	0,013
X5: Hedonic Motivation (HM) -> Y1: Use Behavior (UB)	0,034	0,973
X5: Hedonic Motivation (HM) -> Z1: Behavioral Intention (BI)	0,035	0,972
X6: Price Value (PV) -> Y1: Use Behavior (UB)	0,789	0,430
X6: Price Value (PV) -> Z1: Behavioral Intention (BI)	0,779	0,436
X7: Habit (HT) -> Y1: Use Behavior (UB)	3,884	0,000
X7: Habit (HT) -> Z1: Behavioral Intention (BI)	1,708	0,088

	T Statistics	P Values
Z1: Behavioral Intention (BI) -> Y1: Use Behavior (UB)	5,523	0,000

Source: Primary Data Processed (2024)

3.5 The results of the research hypothesis testing are explained as follows:

Hypothesis H1
The hypothesis test results show that the effect of Performance Expectancy on Use Behavior has a T statistic value of 0.0551 and a P value of 0.582. The T statistic < T table (0.551 < 1.954) and P value > alpha standard 5% (0.582 > 0.05) indicate that there is no effect of Performance Expectancy on Use Behavior. In other words, improved Performance Expectancy does not increase Use Behavior.

Hypothesis H2
The hypothesis test results show that the effect of Performance Expectancy on Behavioral Intention has a T statistic value of 0.577 and a P value of 0.564. The T statistic < T table (0.577 < 1.954) and P value > alpha standard 5% (0.564 > 0.05) indicate that there is no effect of Performance Expectancy on Behavioral Intention. In other words, improved Performance Expectancy does not increase Behavioral Intention.

Hypothesis H3
The hypothesis test results show that the effect of Effort Expectancy on Use Behavior has a T statistic value of 2.092 and a P value of 0.037. The T statistic > T table (2.092 > 1.954) and P value < alpha standard 5% (0.037 < 0.05) indicate a significant effect of Effort Expectancy on Use Behavior. Thus, it can be concluded that Effort Expectancy significantly influences Use Behavior. In other words, improved Effort Expectancy increases Use Behavior.

Hypothesis H4
The hypothesis test results show that the effect of Effort Expectancy on Behavioral Intention has a T statistic value of 2.676 and a P value of 0.008. The T statistic > T table (2.676 > 1.954) and P value < alpha standard 5% (0.008 < 0.05) indicate a significant effect of Effort Expectancy on Behavioral Intention. In other words, improved Effort Expectancy increases Behavioral Intention.

Hypothesis H5
The hypothesis test results show that the effect of Social Influence on Use Behavior has a T statistic value of 0.552 and a P value of 0.581. The T statistic < T table (0.552 < 1.954) and P value > alpha standard 5% (0.581 > 0.05) indicate that there is no effect of Social Influence on Use Behavior. In other words, improved Social Influence does not increase Use Behavior.

Hypothesis H6
The hypothesis test results show that the effect of Social Influence on Behavioral Intention has a T statistic value of 0.539 and a P value of 0.590. The T statistic < T table (0.539 < 1.954) and P value > alpha standard 5% (0.590 > 0.05) indicate that there is no effect of Social Influence on Behavioral Intention. In other words, improved Social Influence does not increase Behavioral Intention.

Hypothesis H7
The hypothesis test results show that the effect of Facilitating Conditions on Use Behavior has a T statistic value of 4.834 and a P value of 0.000. The T statistic > T table (4.834 > 1.954) and P value < alpha standard 5% (0.000 < 0.05) indicate a significant effect of Facilitating Conditions on Use Behavior. In other words, improved Facilitating Conditions increase Use Behavior.

Hypothesis H8
The hypothesis test results show that the effect of Facilitating Conditions on Behavioral Intention has a T statistic value of 2.497 and a P value of 0.013. The T statistic > T table (2.497 > 1.954) and P value < alpha standard 5% (0.013 < 0.05) indicate a significant effect of Facilitating Conditions on Behavioral Intention. In other words, improved Facilitating Conditions increase Behavioral Intention.

Hypothesis H9
The hypothesis test results show that the effect of Hedonic Motivation on Use Behavior has a T statistic value of 0.034 and a P value of 0.973.

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The T statistic < T table (0.034 < 1.954) and P value > alpha standard 5% (0.973 > 0.05) indicate that there is no effect of Hedonic Motivation on Use Behavior. In other words, improved Hedonic Motivation does not increase Use Behavior.

Hypothesis H10
The hypothesis test results show that the effect of Hedonic Motivation on Behavioral Intention has a T statistic value of 0.035 and a P value of 0.972. The T statistic < T table (0.035 < 1.954) and P value > alpha standard 5% (0.972 > 0.05) indicate that there is no effect of Hedonic Motivation on Behavioral Intention. In other words, improved Hedonic Motivation does not increase Behavioral Intention.

Hypothesis H11
The hypothesis test results show that the effect of Price Value on Use Behavior has a T statistic value of 0.789 and a P value of 0.430. The T statistic < T table (0.789 < 1.954) and P value > alpha standard 5% (0.430 > 0.05) indicate that there is no effect of Price Value on Use Behavior. In other words, improved Price Value does not increase Use Behavior.

Hypothesis H12
The hypothesis test results show that the effect of Price Value on Behavioral Intention has a T statistic value of 0.779 and a P value of 0.436. The T statistic < T table (0.779 < 1.954) and P value > alpha standard 5% (0.436 > 0.05) indicate that there is no effect of Price Value on Behavioral Intention. In other words, improved Price Value does not increase Behavioral Intention.

Hypothesis H13
The hypothesis test results show that the effect of Habit on Use Behavior has a T statistic value of 3.884 and a P value of 0.000. The T statistic > T table (3.884 > 1.954) and P value < alpha standard 5% (0.000 < 0.05) indicate a significant effect of Habit on Use Behavior. In other words, improved Habit increases Use Behavior.

Hypothesis H14
The hypothesis test results show that the effect of Habit on Behavioral Intention has a T statistic value of 1.708 and a P value of 0.088. The T statistic < T table (1.708 < 1.954) and P value > alpha standard 5% (0.088 > 0.05) indicate that there is no effect of Habit on Behavioral Intention. In other words, improved Habit does not increase Behavioral Intention.

Hypothesis H15
The hypothesis test results show that the effect of Behavioral Intention on Use Behavior has a T statistic value of 5.523 and a P value of 0.000. The T statistic > T table (5.523 > 1.954) and P value < alpha standard 5% (0.000 < 0.05) indicate a significant effect of Behavioral Intention on Use Behavior. In other words, improved Behavioral Intention increases Use Behavior.

3.6 Discussion

The Influence of Performance Expectancy on Use Behavior
The research results show that the T-statistic value is 0.551 and the P-value is 0.582. The T-statistic value is less than the T-table (0.551 < 1.954), and the P-value is greater than the 5% alpha standard (0.582 > 0.05), indicating that there is no influence of Performance Expectancy on Use Behavior. In other words, higher Performance Expectancy does not increase Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Performance Expectancy on Behavioral Intention
The research results show that the T-statistic value is 0.577 and the P-value is 0.564. The T-statistic value is less than the T-table (0.577 < 1.954), and the P-value is greater than the 5% alpha standard (0.564 > 0.05), indicating that there is no influence of Performance Expectancy on Behavioral Intention. In other words, higher Performance Expectancy does not increase Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Effort Expectancy on Use Behavior
The research results show that the T-statistic value is 2.092 and the P-value is 0.037. The T-

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statistic value is greater than the T-table (2.092 > 1.954), and the P-value is less than the 5% alpha standard (0.037 < 0.05), indicating a significant influence of Effort Expectancy on Use Behavior. In other words, higher Effort Expectancy increases Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Effort Expectancy on Behavioral Intention

The research results show that the T-statistic value is 2.676 and the P-value is 0.008. The T-statistic value is greater than the T-table (2.676 > 1.954), and the P-value is less than the 5% alpha standard (0.008 < 0.05), indicating a significant influence of Effort Expectancy on Behavioral Intention. In other words, higher Effort Expectancy increases Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Social Influence on Use Behavior

The research results show that the T-statistic value is 0.552 and the P-value is 0.581. The T-statistic value is less than the T-table (0.581 < 1.954), and the P-value is greater than the 5% alpha standard (0.581 > 0.05), indicating no influence of Social Influence on Use Behavior. In other words, higher Social Influence does not increase Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Social Influence on Behavioral Intention

The research results show that the T-statistic value is 0.539 and the P-value is 0.590. The T-statistic value is less than the T-table (0.539 < 1.954), and the P-value is greater than the 5% alpha standard (0.590 > 0.05), indicating no influence of Social Influence on Behavioral Intention. In other words, higher Social Influence does not increase Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Facilitating Conditions on Use Behavior

The research results show that the T-statistic value is 4.834 and the P-value is 0.000. The T-statistic value is greater than the T-table (4.834 > 1.954), and the P-value is less than the 5% alpha standard (0.000 < 0.05), indicating a significant influence of Facilitating Conditions on Use Behavior. In other words, better Facilitating Conditions increase Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Facilitating Conditions on Behavioral Intention

The research results show that the T-statistic value is 2.497 and the P-value is 0.013. The T-statistic value is greater than the T-table (2.497 > 1.954), and the P-value is less than the 5% alpha standard (0.013 < 0.05), indicating a significant influence of Facilitating Conditions on Behavioral Intention. In other words, better Facilitating Conditions increase Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Hedonic Motivation on Use Behavior

The research results show that the T-statistic value is 0.034 and the P-value is 0.973. The T-statistic value is less than the T-table (0.034 < 1.954), and the P-value is greater than the 5% alpha standard (0.973 > 0.05), indicating no influence of Hedonic Motivation on Use Behavior. In other words, higher Hedonic Motivation does not increase Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Hedonic Motivation on Behavioral Intention

The research results show that the T-statistic value is 0.035 and the P-value is 0.972. The T-

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statistic value is less than the T-table (0.035 < 1.954), and the P-value is greater than the 5% alpha standard (0.972 > 0.05), indicating no influence of Hedonic Motivation on Behavioral Intention. In other words, higher Hedonic Motivation does not increase Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Price Value on Use Behavior
The research results show that the T-statistic value is 0.789 and the P-value is 0.430. The T-statistic value is less than the T-table (0.789 < 1.954), and the P-value is greater than the 5% alpha standard (0.430 > 0.05), indicating no influence of Price Value on Use Behavior. In other words, higher Price Value does not increase Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Price Value on Behavioral Intention
The research results show that the T-statistic value is 0.779 and the P-value is 0.436. The T-statistic value is less than the T-table (0.779 < 1.954), and the P-value is greater than the 5% alpha standard (0.436 > 0.05), indicating no influence of Price Value on Behavioral Intention. In other words, higher Price Value does not increase Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Habit on Use Behavior
The research results show that the T-statistic value is 3.884 and the P-value is 0.000. The T-statistic value is greater than the T-table (3.884 > 1.954), and the P-value is less than the 5% alpha standard (0.000 < 0.05), indicating a significant influence of Habit on Use Behavior. In other words, stronger Habit increases Use Behavior. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Habit on Behavioral Intention
The research results show that the T-statistic value is 3.745 and the P-value is 0.000. The T-statistic value is greater than the T-table (3.745 > 1.954), and the P-value is less than the 5% alpha standard (0.000 < 0.05), indicating a significant influence of Habit on Behavioral Intention. In other words, stronger Habit increases Behavioral Intention. This result aligns with studies by (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

The Influence of Behavioral Intention on Use Behavior
The research results indicate that the T-statistic value is 5.523 and the P-value is 0.000. The T-statistic value is greater than the T-table (5.523 > 1.954), and the P-value is less than the 5% alpha standard (0.000 < 0.05), indicating a significant influence of Behavioral Intention on Use Behavior. In other words, higher Behavioral Intention can increase Use Behavior. This finding is supported by studies from (Pangestu, 2022); (Febriani et al., 2023); (Rizally et al., 2023); (Desvira & Aransyah, 2023); (Andini & Hariyanti, 2021).

4 Conclusion

Based on the research findings, it can be concluded that certain factors considered to influence use behavior and behavioral intention in a specific context do not have a significant effect. Specifically, Performance Expectancy, Social Influence, Hedonic Motivation, and Price Value do not show a strong relationship with either Use Behavior or Behavioral Intention, indicating that performance expectations, social motivation, hedonic motivation, and perceived price value are not the primary driving factors affecting use behavior or the intention to use within the context of this study. However, the study reveals that Effort Expectancy and Facilitating Conditions play an important role in increasing Use Behavior and Behavioral Intention, suggesting that ease of use and supporting conditions are key in motivating user behavior and intention. Habit is also found to influence Use Behavior, though not significantly impacting Behavioral Intention, which could mean that habitual use strengthens actual behavior even if it does not always reinforce initial intent or desire. Additionally, Behavioral Intention has a significant effect on Use Behavior, confirming that strong intention tends to trigger actual behavior.

From these findings, future development can focus on designing strategies that enhance Effort Expectancy and Facilitating Conditions, for instance, by providing supportive resources and training that ensure an efficient user experience. Furthermore, future research could explore new variables or other contexts where Performance Expectancy or Social Influence might play a greater role. Practical applications of this research can be implemented in the development of systems that require efficiency and ease for users, particularly in work or educational environments where ease of use and facility support play a crucial role in encouraging technology adoption or new practices.

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