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Measuring the Acceptance Level of the Warehouse Module Using the Extended Unified Theory of Acceptance and Use of Technology Model

Sarmini[1*], Kholiq Budiman[2]
[1,2] Department of Computer Science, Faculty of Mathematics and Natural Sciences, Universitas Negeri Semarang, Semarang, Indonesia
*Corresponding Author: sarmini282@students.unnes.ac.id

ABSTRACT

This study aims to measure the acceptance level of the warehouse module within the ERP system implemented at CV Kalingga Keling Jati, utilizing the extended UTAUT model. The analyzed variables include performance expectancy, effort expectancy, hedonic motivation, trust, behavioral intention, use behavior, and one moderator variable, education. The results indicate that effort expectancy, hedonic motivation, trust, and behavioral intention significantly influence users' intention and behavior in utilizing the warehouse module. However, performance expectancy and the moderator variable education do not show significant influence. This research also highlights the importance of effective warehouse management systems to minimize errors in inventory management and enhance operational efficiency within the company. With the implementation of an ERP system integrated with IoT, CV Kalingga Keling Jati aims to improve user satisfaction and reduce resistance to new technologies. The findings provide insights for other companies considering similar technology adoptions in their warehouse management.Furthermore, the study emphasizes the need for continuous evaluation and adaptation of technology to align with user needs and organizational goals. By understanding user acceptance, organizations can better tailor their systems to enhance productivity and foster a positive technological environment. This study contributes to a deeper understanding of the factors influencing technology acceptance in the business context, particularly in the manufacturing sector, and offers a foundation for future system improvements.

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1. INTRODUCTION

In recent years, business process management technology has been progressively adopted in line with the increasing number of existing business processes (Pamungkas et al., 2014). The adoption of technology in business processes certainly facilitates companies in running their business operations. One form of technology adoption in business processes is the implementation of the technology to transition from manual systems to support their business processes. One of the critical aspects that must be considered in a manufacturing company is the warehouse. The warehouse is used to store raw material inventories that are used in the production process. The warehouse must given attention to minimize errors in raw material inventory or finished goods inventory after the production process. Common errors in warehousing include delays in the delivery of raw materials, which can often occur due to inefficiencies in inventory management or errors in order processing. Information technology issues can also become obstacles if the technology used is inadequate for warehouse management. Typical problems arising from these issues include data inaccuracies or slow processes. In addition to the aforementioned problems, security issues can also occur in the warehouse, such as missing or damaged goods.

The issues mentioned above can be addressed by creating a system that effectively manages the warehouse. This system will help those dealing with the warehouse to control inventory more easily, thereby minimizing the aforementioned problems. Implementing an ERP system integrated with IoT can be a solution to these issues, as demonstrated by CV Kalingga Keling Jati. CV Kalingga Keling Jati is a furniture company located in Jepara Regency, Central Java Province. In conducting its business activities, the company is relatively new to using an ERP system, having previously relied on manual systems. The new technology used by CV Kalingga Keling Jati involves the integration of IoT in the warehouse module of the ERP system. With the transition from manual to technology-based systems, CV Kalingga Keling Jati needs to adapt to using this new technology, making it necessary to measure the acceptance level of the newly integrated system. This measurement is carried out to understand how well users accept and are satisfied with the quality and performance of the developed system. If the system is not measured, it can lead to issues such as user resistance and rejection of the new system, rendering the newly developed system useless. Additionally, another problem that may arise from the lack of measurement is the absence of user feedback, leaving developers unaware of the issues or improvements needed for the system.

Enterprise Resource Planning (ERP) is a type of information technology development used in managing company resources, which was previously known as a basic mathematical calculation application or Management Resource Planning

(MRP) (Darmaningrat et al., 2019). Among the various supporting technologies available for businesses, ERP systems are one of the ways to automate business activities and improve process management (Putra & Wahyu, 2022). ERP functions as the backbone of interrelated cross-functional companies and can enhance various internal business processes and information systems in the departments of production, distribution, logistics, accounting, finance, and human resources within a company (Keong et al., 2012).

Research related to the use of the extended UTAUT model to measure user acceptance of ERP systems was conducted by Billyan dan Irawan (2021) who added two additional variables, namely trust and learning value. However, these two additional variables do not have a significant effect on the acceptance of Application Systems and Products in Data Processing (SAP) ERP technology. Then, the research revealed that the variables that had a significant influence on the acceptance of SAP ERP technology were hedonic motivation, price value, and habits. Then, other research was also conducted by Uddin *et al*. (2019), this research adds additional variables such as education and firm size. This research shows that the variables performance expectancy, effort expectancy, social influence, and facilitating conditions have a significant effect on the intention to use ERP. Meanwhile, the variables education and firm size have no effect on ERP acceptance by users.

The extended UTAUT model is used because it is a contemporary technology adoption theory and has the best predictive power among all models (Indrawati & Putri, 2018). The variables used in this study are performance expectancy (PE), effort expectancy (EE), hedonic motivation (HM), and additional external variables, namely trust and education. It has been consistently proven that utility-related constructs, such as performance expectancy, are the most reliable indicators of behavioral intention (Venkatesh et al., 2003). Effort expectancy is defined as the degree of ease associated with the use of a system (Venkatesh et al., 2003), while hedonic motivation is defined as the pleasure or satisfaction derived from using technology and has been shown to play an important role in determining technology acceptance (Brown & Venkatesh, 2005). Next, the external variable trust is used to determine the confidence in using the technology and to foster mutual dependence (Billyan & Irawan, 2021). The education variable impacts users' opportunities, preferences, and decisions regarding the system (Uddin et al., 2019). Therefore, this variable may influence users' choices in using and adopting technology (Mao et al., 2019). These variables were selected because they closely represent the activities occurring at CV Kalingga Keling Jati. Thus, if any variable is found to be insignificant, it can serve as a basis for the company to evaluate and improve its systems and resources.

Research related to the use of the extended UTAUT model to measure user acceptance of ERP systems was conducted by Billyan & Irawan (2021), who added two additional variables: trust and learning value. However, these two additional variables did not significantly affect the acceptance of Systems Application and Products in Data Processing (SAP) ERP technology. The study revealed that the variables significantly influencing the acceptance of SAP ERP technology were hedonic motivation, price value, and habit. Additionally, another study conducted by Uddin et al. (2019)added additional variables such as education and firm size. The study showed that the variables performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influenced the intention to use ERP. However, the variables education and firm size did not affect the acceptance of ERP by users.

Apart from the research above, Handoko dan Prianto (2020) research entitled "The Influence of UTAUT on ERP Systems in Start-up Business" also examines the acceptance of ERP systems using the UTAUT model. This research still uses the UTAUT model which has not been expanded. The research results show that the use of ERP systems in startup businesses supports user needs. Variables that have a significant influence are performance expectancy, effort expectancy, facilitating conditions, and significant use behavior.

With the advancement of technology, manufacturing companies need to adopt effective systems for warehouse management to reduce errors in inventory management and enhance operational efficiency. CV Kalingga Keling Jati implemented an ERP system equipped with an IoT-based warehouse module to facilitate their warehouse management. This study aims to measuring the acceptance level of the warehouse module in the ERP system at CV Kalingga Keling Jati and determine the factors that influence users’ intention and behavior in using the warehouse module.

2. RESEARCH FRAMEWORK

2.1 RESEARCH METODOLOGY

The procedure and method implemented in this research are presented in Figure 1 below.

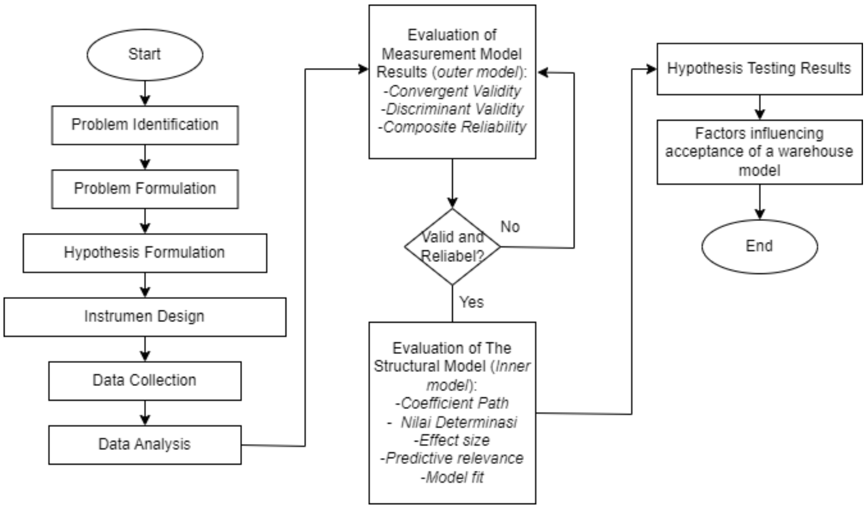

Figure 1. Research Design

In figure 1, the initial of the research can be seen, starting with problem identification to determine the factors influencing the acceptance of the warehouse module, which will then be formulated as the basis for the research to be conducted. Next, hypothesis will be established and research instruments will be created based on the extended UTAUT model. Before the research instruments are distributed, they will be validated to ensure their suitability by reviewing previous studies as references. Once the instruments are validated, they will be distributed to collect data. After the required data is collected, data analysis will be conducted using the outer model and inner model methods. Subsequently, if the data is valid, hypothesis testing will be performed using PLS-SEM with the extended UTAUT model with the help of SmartPLS software. Finally, conclusions will be drawn based on the hypothesis testing that has been carried out.

2.2 HYPOTHESIS METHODOLOGY

In this section, the research model will be presented and can be seen in Figure 2.

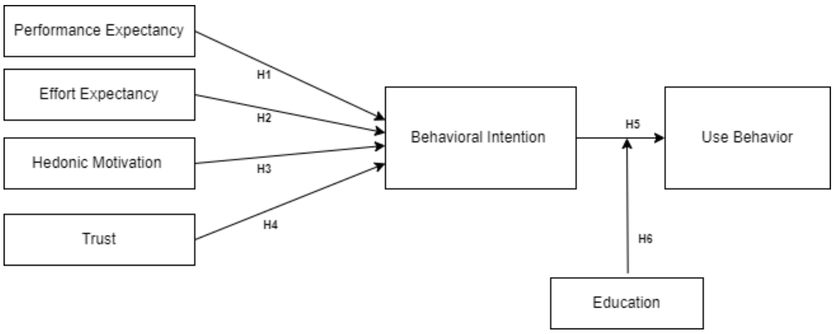

Figure 2. Research Model

- Performance expectancy significantly influences behavioral intention.
- Effort expectancy significantly influences behavioral intention.
- Hedonic motivation significantly influences behavioral intention.
- Trust significantly influences behavioral intention.
- Behavioral intention significantly influences use behavior.
- Moderating effect significantly influences use behavior.

2.3 DATA COLLECTION AND DATA ANALYSIS

The data needed to measure the acceptance of the warehouse module in this study were collected from employees of CV Kalingga Keling Jati who are involved in using the warehouse module system through a questionnaire. The data used were obtained from employees in the warehouse division, as they are the ones who understand and operate the warehouse module system. This study does not employ sampling techniques; instead, it applies total sampling to enhance confidence.

Therefore, the sample used in this research consists of the entire population, which in this case is the users of the warehouse module, totaling 30 employees. According to Waty et al. (2021), the Partial Least Squares (PLS) analysis is recognized for its robustness in analyzing data because it does not require data to be on a specific scale and allows for the use of relatively small samples, ranging from 30 to 100 observations. Gefen et al. (2000) also indicated that in PLS, small sample sizes are acceptable with a minimum ratio of 5 observations per latent variable. This means that with a sample size of 30, PLS analysis can be conducted as long as there are no more than 6 latent variables. This approach aligns with the proposed model in this study, which includes 6 latent variables: performance expectancy, effort expectancy, hedonic motivation, trust, behavioral intention, and use behavior.

Data collection is conducted by creating instruments derived from variables based on the extended UTAUT model. These instruments will be used in questionnaires that can be filled out using a Likert scale. According to Djaali and Muljono (2008), the Likert scale is a tool that can be used to measure the attitudes, opinions, and perceptions of individuals or groups towards an educational phenomenon or phenomenon. Each instrument item will be measured on an interval from 1 (one) to 5 (five). However, data analysis is conducted using the outer model and inner model. The outer model involves validity and reliability tests, while the inner model is analyzed based on path coefficient testing, R-square, f-square, Q-square, and model fit tests.

3. RESULTS AND DISCUSSION

We assigned unique values to the education factors (1= senior high school, 2= diploma, 3= bachelor, 4= magister). The results of the data analysis of 30 respondents based on their highest level of education show that 15 people (50%) have a high school education, 4 people (13%) have a diploma, and 11 people (37%) have a bachelor's. Figure 3 illustrates the demographic analysis results based on educational level.

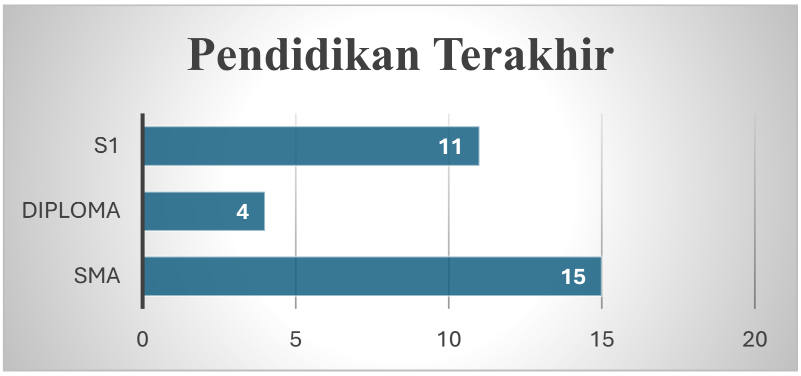

Figure 3. Results of Demographic Analysis Based on Educational Level

Before conducting the outer model analysis, the mean, minimum (min), maximum (max), and standard deviation of each indicator variable will first be calculated for descriptive analysis. This is to characterize the acceptance level of the warehouse module in the ERP system. The acceptance level based on the mean, min, max, and standard deviation values can be seen in Table 1.

Table 1. Acceptance Level Category

Variable	N	Mean	Min	Max	Standard Deviation
Performance expectancy	30	3,99	1	5	0,447
Effort expectancy	30	3,92	2	5	0,359
Hedonic motivation	30	3,96	2	5	0,436
Trust	30	4,05	1	5	0,442

Variable	N	Mean	Min	Max	Standard Deviation
Behavioral intention	30	3,77	2	5	0,433
Use behavior	30	3,87	1	5	0,447

Table 1 shows that the average value of the performance expectancy variable is 3,99, indicating that the warehouse module's user acceptance is in the good category. This analysis also shows that the performance expectancy variable's standard deviation is 0,447, which indicates that it satisfies the requirement that the standard deviation value be less than the mean value, indicating that the data distribution is uniform. The lower bound or minimum value obtained from this analysis is 1, and the upper bound or maximum value is 5.

Furthermore, for the effort expectancy variable, a mean value of 3,92 was obtained, which is categorized as good, and a standard deviation value of 0,359 was obtained. The standard deviation for this variable meets the requirements, indicating that the data is uniformly distributed. These values show that users have confidence in the system. Users believe that they can easily learn the warehouse module. They also believe that the warehouse module is user-friendly. Additionally, they are confident that the warehouse module is easy to use and that they will easily acquire the skills to use the module.

The mean value of the hedonic motivation variable is 3,96, which means this variable is accepted by users in the good category. The standard deviation obtained is 0,436 and meets the requirements. Given that the standard deviation is lower than the mean value of the variable, it indicates that the data is uniformly distributed. Based on the mean value obtained, it means that users agree that the warehouse module can give them pleasure in using it. They also agree that the warehouse module is engaging and can provide satisfaction in their work.

The trust variable in this study obtained a mean value of 4,05 and a standard deviation of 0,442. The standard deviation meets the requirements as it is lower than the mean value. Based on these values, it can be categorized as good, which means that users of the warehouse module agree that the warehouse module is reliable, useful in their work, and also facilitates their tasks. Additionally, users believe that the warehouse module is a safe system to use for assisting with their work.

The behavioral intention variable, as an intermediary variable between performance expectancy, effort expectancy, hedonic motivation, and trust with the dependent variable use behavior, received a mean value of 3,77 and a standard deviation of 0,433. The mean value obtained indicates that user acceptance of the warehouse module is categorized as good, meaning that users are likely to use the warehouse module in the next three months. They will also use the warehouse module regularly. This may be due to several factors, such as the ERP system being very new to the company, so the process of adoption or getting accustomed to using the system naturally takes time.

The use behavior variable, as the dependent variable, received a mean value of 3,87 and a standard deviation of 0,477, indicating that the warehouse module is well-accepted. The standard deviation value obtained is smaller than the mean value, which means the data is uniformly distributed.

3.1 Measurement Model Evaluation

In order to test for convergent validity, the Average Variance Extracted (AVE) values for each variable are examined. Values above 0,7 are deemed adequate and high, while values below 0,5 are deemed sufficient.

Table 1. Average Variance Extracted

Variable	AVE
Performance expectancy	0,622
Effort expectancy	0,511
Hedonic motivation	0,598
Trust	0,574
Behavioral intention	0,575
Use behavior	0,606

Based on Table 2, the AVE values for all latent variables are above 0,5, indicating that these variables are considered valid. In addition to AVE values, this test also considers the loading factor values. The minimum loading factor value is 0,7 (J. F. Hair et al., 2017). However, this study uses a minimum outer loading value of 0,6 (Chin, 1998).

Table 3. Outer Loading

	BI	EE	HM	PE	TR	UB
BI2	0,750					
BI3	0,698					
BI4	0,823					
EE1		0,618				
EE2		0,694				
EE3		0,729				
EE4		0,758				

	BI	EE	HM	PE	TR	UB
EE5		0,654				
EE6		0,819				
HM1			0,848			
HM2			0,761			
HM4			0,704			
PE1				0,641		
PE3				0,822		
PE5				0882		
TR1					0,826	
TR2					0,676	
TR4					0,764	
UB1						0,696
UB3						0,804
UB4						0,830

Next, discriminant validity testing will be conducted. The discriminant validity test can be assessed based on the cross-loading values obtained. Each indicator's cross-loading value should correlate more strongly with its own latent variable than with other latent variables. Table 4 shows the results of the discriminant validity test in this study.

Table 2. Cross Loading

	BI	EE	HM	PE	TR	UB
BI2	0,750	0,647	0,641	0, 249	0,644	0,650
BI3	0,698	0,555	0,337	0,413	0,222	0,504
BI4	0,823	0,679	0,608	0,335	0,244	0,675
EE1	0,574	0,618	0,436	0,338	0,512	0,666
EE2	0,436	0,694	0,509	0,058	0,686	0,494
EE3	0,487	0,729	0,439	0,176	0,435	0,546
EE4	0,618	0,758	0,510	0,318	0,535	0,757
EE5	0,628	0,654	0,260	0,431	0,195	0,455
EE6	0,730	0,819	0,643	0,339	0,444	0,594
HM1	0,658	0,747	0,848	0,221	0,748	0,734
HM2	0,460	0,321	0,761	0,136	0,549	0,357
HM4	0,503	0,377	0,704	0,015	0,531	0,414
PE1	0,155	0,199	-0,031	0,641	-0,060	-0,010
PE3	0,353	0,308	0,087	0,822	0,044	0,419
PE5	0,423	0,408	0,246	0882	0,125	0,349
TR1	0,480	0,562	0,632	0,025	0,826	0,554
TR2	0,233	0,333	0,540	0,123	0,676	0,161
TR4	0,317	0,499	0,658	0,066	0,764	0,430

	BI	EE	HM	PE	TR	UB
UB1	0,592	0,623	0,497	0,501	0,484	0,696
UB3	0,632	0,627	0,522	0,169	0,329	0,804
UB4	0,669	0,676	0,563	0,260	0,488	0,830

The cross-loading values for each variable in Table 4 are higher than their correlations with other variables, indicating that these variables meet discriminant validity criteria. However, the cross-loading value obtained for the EE variable, specifically indicator EE1, is lower than the correlation of indicator EE1 with UB, which is valued 666. Therefore, this study decides to remove that indicator because it does not meet discriminant validity criteria. Thus, the variables have met the requirements for discriminant validity testing.

Next, consistency reliability testing will be conducted. This testing is based on Cronbach's alpha and composite reliability values. According to Darma (2021), the acceptable minimum value for Cronbach's alpha is 0,6, while the minimum acceptable value for composite reliability is 0,7. Based on the test results, Table 5 shows the values of Cronbach's alpha and composite reliability for each variable.

Table 3. Cronbach's Alpha and Composite Reliability

Variable	Cronbach's Alpha	Composite Reliability
Behavioral intention	0,633	0,802
Education	1,000	1,000
Effort expectancy	0,808	0,862
Hedonic motivation	0,665	0,816
Performance expectancy	0,713	0,829
Trust	0,655	0,801
Use behavior	0,672	0,821

The minimum acceptable value for Cronbach's alpha is 0,6. Therefore, in Table 5 all variables are considered reliable as they have reached the minimum value. Additionally, the table shows that the composite reliability values meet the required minimum threshold, indicating that they are reliable and suitable for further testing.

3.2 Structure Model Evaluation

This test is evaluated based on p-values and t-statistics. The test uses a significance level of 5%, meaning that p-values should not exceed 0,05. The test also uses t-statistics, which must be greater than 1,96. Additionally, the test is assessed based on the original sample value, where the positive or negative value can influence the hypothesis. The results of the coefficient path testing are presented in Table 6.

Table 4. Coefficient Path

Hipotesis	Path	Original Sample	t-statistics	p-values	Description
H1	PE → BI	0,084	0,903	0,367	Rejected
H2	EE → BI	0,676	4,575	0,000	Accepted
H3	HM → BI	0,599	2,906	0,004	Accepted
H4	TR → BI	-0,432	1,985	0,048	Accepted
H5	BI → UB	0,808	10,872	0,000	Accepted
H6	EDU → UB	-0,197	1,917	0,056	Rejected
	Moderating Effect 1 → UB	0,054	0,406	0,685	Rejected

Next, model testing will be conducted using the determination test (R^2). This test is used to determine the extent to which endogenous variables are influenced by other variables by looking at the R^2 value. According to Hair *et al*. (2017), an R^2 value is considered strong if it is 0,75, moderate if it is 0,50, and weak if it is 0,25. Table 7 shows the results of the R^2 test.

Table 5. R-squared

	R-squared
Behavioral intention	0,772
Use behavior	0,702

The R^2 value of the BI variable in Table 7 indicates a strong value as it meets the criteria and is greater than 0,75, while the R^2 value of the UB variable indicates a value less than 0,75, thus it can be considered moderate. After the R^2 testing, the next step is to conduct an effect size test. This test is performed to determine whether an independent latent variable has a significant impact on a dependent latent variable (Purnomo & Indriyanti, 2023). Yamin and Kurniawan (2011) state that the acceptable f^2 value has three criteria: 0,02 (small), 0,15 (medium), and 0,35 (large). However, Kelly (2018) reveals that the f^2 value for moderation tests has several criteria: 0,005 (low), 0,01 (moderate), and 0,025 (high) (Hamilton, 2015). Table 8 shows the effect size values from this study.

Table 6. Effect Size

Variable relationships	f^2	Description
BI→UB	2,141	High

EE→BI	0,683	High
HM→BI	0,519	High
PE→BI	0,071	Small
TR→BI	0,178	Medium
EDU→UB	0,129	Medium
Moderating Effect→UB	0,010	Moderate

Based on Table 8, it can be seen that the correlation variables BI with UB, EE with BI, and HM with BI have a large impact. The correlation variable PE with BI has a small impact. Then, the correlation variables that have a medium impact are the correlation variables TR with BI and EDU with UB, while the moderation effect correlation with UB has a moderate impact.

The next test is the Q^2 test. This test is conducted using the blindfolding method. There are three criteria for the Q^2 test: greater than 0,35 (large), between 0,02-0,25 (medium), and less than 0,02 (small). Table 9 shows the results of the Q^2 test.

Table 7. Q-squared

	Q-squared
Use behavior	0,389
Behavioral intention	0,345

Table 9 shows that the Q^2 value for the UB variable is 0,389, which is greater than 0,35 and considered large, while the BI variable has a Q^2 value in the medium range, specifically 0,345. Thus, this test indicates that the research model can predict endogenous variables with other exogenous variables with fairly good observed values.

The model fit test is conducted to measure the extent to which the research model provides information on how well the model can explain the relationships between variables. According to Hair et al. (2021), this test is considered to have a good fit if it has a value below 0,08. However, Schermelleh-Engel dan Moosbrugger (2003) state that to achieve a good fit, the SRMR value should be below 0,10. Therefore, this study uses an SRMR value threshold of 0,10. Table 10 shows the results of the SRMR values.

Table 8. Goodness of Fit Model

Index	Batas	Value
SRMR	≤ 0,10	0,135
Chi-square	≥ 0,05	431,374
NFI	≥ 0,90	0,322

The SRMR value in Table 10 indicates a figure that exceeds the specified threshold, with a value of 0,135. Based on the SRMR value, the proposed research model does not meet the criteria for fit (model fit). However, this value also depends on the sample size used. A larger sample size tends to result in an SRMR value moving towards good fit (Schermelleh-Engel & Moosbrugger, 2003). Meanwhile, based on the chi-square measurement, the model is considered a good fit because it obtains a value ≥ 0,05, whereas based on the NFI measurement, the obtained value is below 0,90, indicating that the model does not meet the criteria for good fit in this measurement.

However, according to Hair et al. (2019), besides using the SRMR value, another way to assess the goodness of fit of a SEM model is through PLS Predict analysis. This analysis examines and compares the RMSE and MAE values between the PLS SEM model and the Latent Model (LM). Table 11 presents the results of the PLS Predict analysis.

Table 9. Test Result of PLS Predict

	PLS SEM Model		LM Model	
	RMSE	MAE	RMSE	MAE
BI3	0,855	0,669	1,125	0,758
BI4	0,576	0,430	1,102	0,858
BI2	0,817	0,655	0,979	0,768
UB4	0,613	0,517	0,668	0,522
UB1	0,857	0,709	2,113	1,561
UB3	0,630	0,497	0,809	0,671

Table 11 shows that the RMSE and MAE values in the PLS SEM model are not greater than those in the LM model. According to Hair et al. (2019), if the values in the PLS SEM model are not greater than those in the LM model, then the model has strong predictive power. Therefore, based on the PLS Predict analysis, this research model falls into the strong category.

4. CONCLUSION

The variables that significantly influence the use behavior variable are effort expectancy (EE), hedonic motivation (HM), trust (TR), and behavioral intention (BI). When users find it easy to use the warehouse module in the ERP system, it will increase their intention to continue using the system. Additionally, the pleasure users derive from using the system can also influence their intention to keep using the warehouse module because they feel happy when using the system, which in turn enhances their performance. Trust in the system is also a factor that can affect users' intention to use the warehouse module continuously. This trust can be in the form of confidence in the security of the data stored in the system or the security of the information presented. Meanwhile, the level of acceptance of the warehouse module in this study is categorized as good based on the mean score obtained, which falls in the class interval of 3,43−4,23. This means that users of the warehouse module are satisfied with the presence of the warehouse module in the company's ERP system.

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