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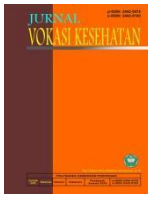

APPLICATION OF UTAUT 3 MODEL TO PREDICT EMR ACCEPTANCE BY NURSES

Annissa Ambaravista Nasution[1], Ermi Girsang[2], Sri Lestari Ramadhani Nasution[3]
[1,2,3]Master of Public Health Study Program, Faculty of Medicine, Dentistry and Health Sciences, Universitas Prima Indonesia, Indonesia.

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Abstract

The implementation of an Electronic Medical Record (EMR) system plays an important role in improving the efficiency and quality of nursing services in hospitals. However, the level of user acceptance, especially nurses, is often a major challenge in its implementation. This study aims to analyze the factors that influence EMR acceptance by nurses at Graha Bunda Hospital using the Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) approach. The method used is quantitative with an explanatory survey design. The study population included all active nurses at Graha Bunda Hospital, totaling 67 people, who were used as respondents through the total sampling technique. Data were collected through questionnaires and analyzed using the Partial Least Square (PLS) method with the help of SmartPLS software. The results of the analysis show that the variables of performance expectancy ($\beta = 0.287$; $p < 0.05$), effort expectancy ($\beta = 0.224$; $p < 0.05$), social influence ($\beta = 0.231$; $p < 0.05$), facilitating conditions ($\beta = 0.265$; $p < 0.05$), hedonic motivation, leadership and management, regulation and policy, technology readiness, and security & privacy have a significant influence on behavioral intention and use behavior. Moderating variables such as age, work experience, and level of volunteerism strengthen some of the relationships between variables. This study suggests that perceived usefulness, ease of use, organizational support, and technology readiness are key factors in EMR adoption. Hospitals need to focus on strengthening training, improving digital infrastructure, and creating a technology-based work culture to encourage optimal sustainability of EMR use.

Correspondence address:
Master of Public Health Study Program, Faculty of Medicine, Medicine Dentistry and Health Sciences, Universitas Prima Indonesia, Indonesia
Email: ermigirsang@unprimdn.ac.id

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Introduction

Application *Electronic Medical Record* (EMR) is an essential aspect in the modernization of health services, especially in improving the efficiency of recording and accessing patient medical data by medical personnel, including nurses. EMRs allow quick access to important information such as disease history, allergies, medications, and test results, thus supporting informed clinical decision-making and lowering the risk of errors due to incomplete information (Kim & Kang, 2023). EMRs help accelerate coordination between professionals in medical services, support real-time information exchange, and encourage safer, high-quality care (Burridge et al., 2018).

In addition to the clinical benefits, EMRs also simplify administrative burdens and speed up services, thereby improving the operational efficiency of hospitals (Devi Delvita & Dety Mulyanti, 2023). The reduction in documentation errors and the reduction of patient waiting times show the positive impact of EMR implementation in healthcare (Mahal Alrehaili & Zayyan Alsharqi, 2021). The application of EMR has even been proven globally to increase productivity, reduce workload, and save costs, while strengthening collaboration between healthcare providers (Liasari et al., 2024; Onigbogi et al., 2018). Nurses also value EMR as a system that facilitates their work, especially in improving communication and coordination of teams between professions (Massora et al., 2024).

EMR plays an important role not only in individual care, but also in supporting approaches *patient-centered care*, especially in service units such as rehabilitation (Squirrel Siregar et al., 2022; Fauziah et al., 2024). However, in developing countries, EMR implementation challenges are still significant, including technological limitations, resistance to change, and the need to adapt to the local context (Ariffin et al., 2018). Studies in Nigeria and Indonesia show that readiness and willingness to use EMRs are directly correlated with improved service quality and cost savings (Amalia et al., 2021).

Nurses, as a profession that is face-to-face with patients for 24 hours, have a critical role in the successful implementation of EMR. Today's generation of nurses is generally familiar with digital technology, so they are better prepared to use computer-based applications and software (Batara et al., 2018). They also understand the strategic benefits of EMRs in accelerating access to information and improving the quality of clinical decision-making (Darmin et al., 2022; Rubiyanti, 2023). EMRs are also thought to support collaboration between professionals and aid in evidence-based care, with features such as clinical reminders and data analysis tools (Susanti et al., 2023; Wahyuni et al., 2021).

Nevertheless, the acceptance of EMRs by nurses is also affected by various barriers. The high learning curve, the already large workload, and resistance from senior colleagues are challenges. Inadequate infrastructure and data security and privacy issues also often hinder the optimal implementation of these systems (O'Donnell et al., 2018). Therefore, it is important for healthcare institutions to provide ongoing training, technical support, and investment in information systems and data protection to ensure the successful implementation of EMR (Rahal et al., 2021).

In responding to these challenges and opportunities, the Model *Unified Theory of Acceptance and Use of Technology 3* (UTAUT3) can be used to predict the level of acceptance of technology by nurses. UTAUT3 is a development of previous models, such as TAM and TPB, which provide a comprehensive approach to analyzing individual and social factors influencing technology adoption (Almarzouqi et al., 2022; Simatupang et al., 2022). Factors such as intrinsic motivation, experience with technology, and the social influence of the work environment are important elements in this framework (Resnawaty et al., 2024).

The advantage of UTAUT3 also lies in its ability to accommodate contextual variables such as habits, hedonistic motivations, and perceptions of value or cost. Habits in the use of technology can accelerate nurses' adaptation to EMR, while the aspect of pleasure and comfort (hedonistic) also increases interest in adopting technology (Hwang et al., 2019). The perception of cost is also no less important, especially for healthcare institutions that operate on a limited budget (Zurynski et al., 2021).

In UTAUT3, the expectation of performance (*Performance expectancy*) and ease of use (*Effort expectancy*) becomes the main predictor of behavioral intentions (*Behavioral Intention*) to use technology. Social factors, such as the support of colleagues or superiors, as well as the condition of support facilities (*Facilitating Condition*) also determines the actual behavior of the user (Oo et al., 2021). The advantage of this model is its flexibility and ability to be empirically validated in a variety of healthcare contexts (Stuart & Scott, 2021).

Graha Bunda General Hospital is a relevant research because the hospital represents the challenge of implementing information technology in regional health facilities, which generally face limited infrastructure and human resources. The implementation of the Electronic Medical Record (EMR) system in this environment does not necessarily run optimally without a comprehensive understanding of the acceptance of end users, in this case nurses, who are at the forefront of health services. Understanding the extent to which nurses receive and use EMRs in hospitals provides valuable input in the development of strategies to increase technology acceptance that are appropriate to local conditions.

This study enriches the local literature related to the implementation of EMR, because so far similar studies have been more conducted in large hospitals, metropolitan cities, or in developed countries. The novelty of this study lies in the application *of the Unified Theory of Acceptance and Use of Technology* 3 (UTAUT3) model in the regional hospital environment, which presents a holistic approach by considering individual, organizational, and technological variables simultaneously. In addition, the use of Structural Equation Modeling – Partial Least Squares (SEM-PLS) provides a more robust analysis of the relationship between latent variables.

However, studies that specifically examine the factors that influence EMR acceptance by nurses in regional hospitals, particularly with the UTAUT3 approach, are still very limited. Therefore, this research is expected to fill the gap and become a reference for the development of information technology policies in the regional health sector. This study aims to analyze the factors that affect the intention and behavior of using Electronic Medical Record (EMR) by nurses at Graha Bunda Hospital using the UTAUT3 approach.

Method

This study uses a quantitative approach with an expplanatory survey design to analyze the extent of nurses' acceptance of the use of the Electronic Medical Record (EMR) system at Graha Bunda General Hospital. The main objective of this study is to identify and explain the relationship between various factors that influence EMR use behavior, both from the individual, organization, and technology sides. The research location was chosen purposively, taking into consideration the availability of infrastructure, the readiness of human resources, and the support of the hospital management. The implementation of the research lasted for three months, starting from June to August 2024.

The study population includes all active nurses at Graha Bunda Hospital, totaling 67 people. Because the number did not reach 100 people, the total sampling technique was used, so that all members of the population were made respondents. The inclusion criteria used include nurses who are actively working, used to using technology, and have at least two years of work experience. Meanwhile, nurses who are on leave or refuse to be respondents are grouped in the exclusion criteria.

The data collection instrument is in the form of a questionnaire compiled based on indicators from the Unified Theory of Acceptance and Use of Technology 3 (UTAUT 3) model. Independent variables include *social influence*, *effort expectancy*, *performance expectancy*, *facilitating condition*, *technology readiness*, *habit*, *price value*, *hedonic motivation*, *regulation and policy*, *leadership and management,* as well as security and privacy factors. The bound variables included behavioral intention and use behavior, while the moderation variables included age, gender, experience, and voluntariness of use.

The data collected consisted of primary data (through questionnaires), secondary data (hospital profiles), and tertiary data from scientific sources. The analysis technique used is Partial Least Square (PLS) with SmartPLS software version 4, which includes the evaluation of the outer model through validity and reliability tests, as well as the inner model to test the predictive strength between latent variables.

Result

Analytical Approach

This study uses the SmartPLS 3.0 application to conduct Partial Least Squares (PLS) analysis. Model evaluation in PLS involves two components, namely theMeasurement Model (Outer Model) - To test the validity and reliability of the measuring tool andthe Structural Model (Inner Model) - To predict the relationship between latent variables.

Evaluation of Measurement Model (Outer Model) of Convergent Validity

Convergent validity testing uses *outer loading* or *loading factor* values. If the *outer loading* value of an indicator is greater than 0.7, then it is widely accepted as an indicator that has high convergent validity. The total *outer loading* of each indicator for the research variable is listed below: The results of *the outer loading* measurement in the reflective indicator show that most of the research indicators have met the requirements as variable measurement indicators because they have *an outer loading* value exceeding 0.7 (*outer loading* > 0.7). Therefore, all indicators are considered valid and suitable for use in the follow-up analysis of this study.

Discriminatory Validity

Discriminant validity is measured using two approaches:

1. Heterotrait-Monotrait Ratio (HTMT) All variables show HTMT values below 0.9, which indicates that all constructs of the variables have good discriminating ability.
2. Average Variance Extracted (AVE) All study variables met the standard of AVE values exceeding 0.5 (AVE > 0.5), as shown in the following table:

Table 1. *Average Variant Extracted (AVE)*

Variable	AVE
Behavioral Intention	0,849
Effort Expectancy	0,853
Experience	0,937
Facilitating Condition	0,941
Habit	0,877
Hedonic Motivation	0,895
Leadership and Management	0,799
Perceived Value	0,826
Performance Expectancy	0,872
Regulation and Policy	0,895
Security & Privacy	0,936
Social Influence	0,898
Technology Readiness	0,884
Use Behavior	0,864
Voluntariness of Use	0,903

Composite Reliability

All variables had a Composite Reliability value (rho_a and rho_c) above 0.7, indicating that all the study variables had high reliability.

Table 2. *Composite Reliability*

	Composite Reliability (rho_a)	*Composite Reliability* (rho_c)
Behavioral Intention	0,911	0,944
Effort Expectancy	0,921	0,946
Experience	0,934	0,968
Facilitating Condition	0,969	0,979
Habit	0,944	0,955
Hedonic Motivation	0,945	0,962
Leadership and Management	0,887	0,923
Perceived Value	0,922	0,934
Performance Expectancy	0,928	0,953
Regulation and Policy	0,947	0,962
Security & Privacy	0,973	0,978
Social Influence	0,946	0,964
Technology Readiness	0,949	0,958
Use Behavior	0,922	0,950
Voluntariness of Use	0,916	0,949

Cronbach's Alpha

All of the study variables showed Cronbach's Alpha values above 0.8, which indicates good reliability for all variables.

Table 3. *Cronbach's Alpha*

	Cronbach's alpha
Behavioral Intention	0,911
Effort Expectancy	0,914
Experience	0,933
Facilitating Condition	0,968
Habit	0,930
Hedonic Motivation	0,941
Leadership and Management	0,875
Perceived Value	0,896
Performance Expectancy	0,926
Regulation and Policy	0,941
Security & Privacy	0,966
Social Influence	0,943
Technology Readiness	0,935
Use Behavior	0,921
Voluntariness of Use	0,894

Evaluation of Structural Model (Inner Model) Path Coefficient Test

The results showed that all the variables in the model had a path coefficient with a positive value, which signifies that the higher the value of the path coefficient from the independent variable to the dependent variable, the stronger the relationship between the two.

Coefficient of Determination Test (R^2)

Table 4. Coefficient of Determination

Variable	**R-Square**	**R-Square Adjusted**
Behavioral Intention	0,846	0,784
Use Behavior	0,697	0,608

The R-Square value for Behavioral Intention of 0.846 indicates that 84.6% of the variation in the variable can be explained by independent variables in the model. While the R-Square value for Use Behavior of 0.697 indicates that 69.7% of variations in Use Behavior can be explained by independent variables.

F-Square Test

The results of the f-square analysis showed that several variables had varying degrees of influence on the intention and behavior of using the EMR system by nurses. The interaction between age and performance expectancy on behavioral intention showed an f-square value of 0.198, which was classified as having a strong influence. Similar things can also be seen in the interaction between age and social influence on behavioral intention, with an f-square value of 0.166. The variable effort expectancy on behavioral intention also showed a strong influence with an f-square value of 0.162. Meanwhile, the security & privacy variable on behavioral intent had an f-square value of 0.141, indicating a moderate influence. The relationship between behavioral intention and use behavior obtained an f-square value of 0.130, also included in the category of moderate influence. These findings indicate that the perception of convenience, age factors, as well as security and privacy aspects are important elements that need to be considered in improving the intentions and behaviors of nurses in using EMR systems.

Hypothesis Test

Of the 26 hypotheses tested, 15 hypotheses were accepted and 11 hypotheses were rejected. The following is the accepted hypothesis, namely H_1: Performance Expectancy has a positive and significant effect on Behavioral Intention (T=3.130, P=0.002). H_2: Effort Expectancy has a positive and significant effect on Behavioral Intention (T=2.359, P=0.018), H_3: Social Influence has a positive and significant effect on Behavioral Intention (T=2.278, P=0.023), H_4: Facilitating Condition has a positive and significant effect on Use Behavior (T=3.070, P=0.002), H_5: Hedonic Motivation has a positive and significant effect on Behavioral Intention (T=4.565, P=0.000), H_8: Habit has a positive and significant effect on Use Behavior (T=2.601, P=0.010), H_9: Leadership and Management has a positive and significant effect on Behavioral Intention (T=5.580, P=0.000), H_{10}: Regulation and Policy has a positive and significant effect on Behavioral Intention (T=4.660, P=0.000), H_{12}: Technology Readiness has a positive and significant effect on Use Behavior (T=2.882, P=0.004), H_{13}: Security & Privacy has a positive and significant effect on Behavioral Intention (T=2.190, P=0.029), H_{15}: Age moderates the effect of Performance Expectancy on Behavioral Intention (T=2.143, P=0.032), H_{17}: Age moderates the effect of Social Influence on Behavioral Intention (T=2.370, P=0.018), H_{21}: Experience moderates the effect of Effort Expectancy on Behavioral Intention (T=3.117, P=0.002), H_{25}: Voluntariness of Use moderates the effect of Technology Readiness on Use Behavior (T=2.584, P=0.010).

Discussion

The Effect of Performance Expectancy on Behavioral Intention

The results of the hypothesis test showed that the *T value of statistics* was 3.130 and *the P value* was 0.002. Table T is a type of distribution used to test hypotheses. This distribution table relies on t-test statistics, and in this study, the table's T-value is 1.668. The *statistical T* value > the T table (3.130 > 1.668), and *the P value* of 0.018 < *the standard* alpha of 5% (0.002< 0.05) showed a significant influence of *Performance Expectancy* on *Behavioral Intention*. A positive path coefficient indicates a positive influence of *Performance Expectancy* on *Behavioral Intention*. Thus, it can be concluded that there is a positive and significant influence of *Performance Expectancy* on *Behavioral Intention*. In other words, *the better Performance Expectancy* is able to increase *the Behavioral Intention* or the first Hypothesis (H_1) is accepted.

Performance Expectancy refers to the extent to which individuals believe that the use of a particular technology will improve their work performance or overall effectiveness. Various studies have shown a positive correlation between *Performance Expectancy* and *Behavioral Intention*, implying that when users see technology as something beneficial, they are more likely to intend to use it.

According to *Unified Theory of Acceptance and Use of Technology* (UTAUT), *Performance Expectancy* reflects the extent to which individuals believe that using a technology will improve their performance in certain tasks (D. Liu et al., 2019). These beliefs have a significant influence on an individual's intention to adopt a new technology, as they are more likely to use systems that they perceive will provide beneficial results. For example, Liu et al.'s research shows that *Performance Expectancy* positively correlated with intention to use physical activity apps, highlighting the role of *Performance Expectancy* in motivating users to interact with health technology.

Further research shows that *Performance Expectancy* not only directly affect *Behavioral Intention*, but also interacts with other factors such as *Effort Expectancy* and *Social Influence*. For example, Chao's study found that both PE and Effort Expectancy had a significant effect on *Behavioral Intention*, which suggests that ease of use complements the perceived benefits of the technology (Chao, 2019). In addition, Kadir and Ismail emphasized that *Performance Expectancy* positively affect *Behavioral Intention* among millennials who adopt online delivery services, emphasizing the importance of perceived benefits in the adoption of technology (Kadir & Ismail, 2022).

Further, the relationship between *Performance Expectancy* and *Behavioral Intention* can be moderated by variables such as Perceived Risk and Trust. For example, Chayomchai's research shows that personal trust and innovation directly affect *Performance Expectancy*, which in turn influenced the intention to use online technology during the COVID-19 pandemic (Chayomchai, 2020). This indicates that although *Performance Expectancy* is a strong predictor of BI, its effectiveness can be strengthened or weakened by individuals' trust in technology and their willingness to innovate.

Important *Performance Expectancy* also extends to the context of the organization. Verhees discusses how performance expectations influence small companies' decisions regarding radical product innovation, which shows the implications *Performance Expectancy* in business strategic decision-making (Verhees et al., 2020). In line with that, Mubarok noted that *Performance Expectancy* significantly affect students' intention to adopt QRIS (*Quick Response Code Indonesian Standard*) in their financial transactions, demonstrating their relevance in the context of education and economics (Mubarok et al., 2023).

Thus, it can be concluded that Performance Expectancy is one of the main factors that drive user intent to adopt technology, although its influence can vary depending on the type of technology used and the characteristics of the user.

The Effect of Effort Expectancy on Behavioral Intention

The results of the hypothesis test showed that the *T value of statistics* was 2.359 and *the P value* was 0.018. Table T is a type of distribution used to test hypotheses. This distribution table relies on t-test statistics, and in this study, the table's T-value is 1.668. The *statistical T* value of the T > table (2.359 > 1.668), and *the P value* of 0.018 < *the standard alpha* of 5% (0.018< 0.05) showed a significant influence of *Effort Expectancy* on *Behavioral Intention*. A positive pathway coefficient indicates a positive influence of *Effort Expectancy* on *Behavioral Intention*. Thus, it can be concluded that there is a positive and significant influence of *Effort Expectancy* on *Behavioral Intention*. In other words, the better *Effort*

Expectancy is able to increase *the Behavioral Intention* or the second Hypothesis (H_2) is accepted.

Effort Expectancy (EE) is an important construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), which states that the perception of ease of use of technology significantly influences the user's behavioral intention to adopt and utilize the technology. Studies have shown a positive correlation between Effort Expectancy and Behavioral Intention in a variety of contexts, indicating that when users find a technology easy to use, they are more likely to intend to take advantage of it.

For example, research by Lee and Song shows that Effort Expectancy, along with other factors such as trust and risk perception, explains most of the variance in behavioral intentions to use new technology services, specifically CeDA services. This confirms the importance of user perception of ease of use in the acceptance of technology (Lee & Song, 2013). In addition, Haengnam et al. emphasized that Effort Expectancy is a significant factor influencing behavioral intent in mobile learning services, suggesting that users' perceptions of ease of use directly affect their willingness to interact with technology (Sung et al., 2015).

Another study by Wichean and Sungsanit focusing on chicken farmers in Thailand also found that Effort Expectancy was the most influential factor in the adoption of poultry farm management systems, reinforcing the idea that the perception of ease of use is crucial in technology adoption decisions (Wichean & Sungsanit, 2022). These findings are consistent with a study by Liu, who notes that Effort Expectancy, along with Performance Expectancy and Social Influence, significantly influences behavioral intent in the context of online shopping for fresh agricultural products (L.-W. Liu et al., 2016).

However, some studies report mixed results regarding the relationship between Effort Expectancy and Behavioral Intention. For example, research by Nejadrezaei et al. found no significant association between Effort Expectancy and intention to adopt pressure irrigation technology in olive growers, suggesting that in certain contexts, other factors may influence more than the perception of ease of use (Nejadrezaei et al., 2018). Research by Handayani and Sudiana also showed that although Performance Expectancy and Social Influence had a significant impact on Behavioral Intention, Effort Expectancy did not show a significant influence in their study of academic information systems (Handayani & Sudiana, 2015).

Although there are mixed findings, consensus in the literature confirms that Effort Expectancy plays an important role in shaping behavioral intentions toward technology adoption. The study by Horas et al. further reinforces this, in which they confirm that both Performance and Effort Expectancy positively affect usage intent, confirming that improving user perceptions of ease of use can facilitate wider acceptance of new technologies (Horas et al., 2023).

As such, Effort Expectancy plays a significant role as a significant predictor in the early adoption of the technology, although its influence may diminish over time, depending on the context of the technology and the demographics of the user.

Social Influence (SI) has a significant influence on Behavioral Intention (BI) with values of T = 2.278 and P = 0.023. SI is a social influence of other individuals that can influence decisions in adopting technology. Cultural effects also contribute to reinforcing this influence. Facilitating Condition (FC) showed a significant influence on Use Behavior (UB) with values T = 3.070 and P = 0.002. FC includes technical support and the availability of resources needed in the use of technology. This support is important in facilitating the adoption of technology. Although some of the results show different findings, the majority of studies support the importance of FC in influencing technology use behavior.

Hedonic Motivation (HM) showed a very significant influence on BI with values of T = 4.565 and P = 0.000. HM reflects the level of pleasure or enjoyment felt in using technology. In various contexts such as e-commerce, education, and tourism, HM plays an important role in encouraging the intention of using technology.

Perceived Value (PV) had no significant effect on BI (T = 0.605; P = 0.545). However, in certain contexts, PV can have an indirect influence on behavioral intent, for example through user satisfaction. On the other hand, there are also studies that do not find a significant direct relationship between PV and BI.

Habit had no significant effect on BI (T = 0.478; P = 0.633). Some studies have shown that the effect of habit on behavioral intent tends to be inconsistent and depends on specific contexts. In fact, in some cases, the relationship can deteriorate over time.

Habit had a significant influence on UB (T = 2.601; P = 0.010). Habitual use drives continuous user engagement. The relationship between habit and intention and behavior is reciprocal, and is influenced by social factors and intrinsic motivations.

Leadership and Management showed a very significant influence on BI (T = 5,580; P = 0.000). Leadership styles such as transformational and servant leadership are able to reduce exit intentions and strengthen positive behavior intentions. Organizational commitment and managerial support also play an important role in this. Regulations and policies have a significant influence on BI (T = 4,660; P = 0.000). Policies that are designed effectively are able to increase behavioral intentions through the perception of justice, relevance, and the formation of social norms.

Technology Readiness (TR) had no significant effect on BI (T = 0.087; P = 0.931). This suggests that although individuals have a high readiness for technology, there are other external factors that can hinder the intention to use the technology. Nevertheless, TR had a significant effect on UB (T = 2.882; P = 0.004). Optimism and innovation that individuals possess can encourage active technology use behavior. Technology readiness is an important factor in supporting the application of technology, especially in the health and education sectors.

Security & Privacy has a significant influence on BI (T = 2,190; P = 0.029). Users tend to have higher intentions in using technology if they feel safe and their privacy is protected. However, there is a contradictory phenomenon where users continue to use technology despite being aware of privacy risks, and this can be mediated by the user's level of trust in the system. No significant effect was found between Security and Privacy on UB (T = 0.313; P = 0.754). This shows that there is a gap between the perception of risk to security and privacy and the actual behavior of using technology.

Age moderated the relationship between Performance Expectancy (PE) and BI (T = 2,143; P = 0.032). Older individuals tend to need additional support in using technology, and this reinforces their intention to participate in the use of technology.

No significant age-related moderation effect was found on the relationship between Effort Expectancy (EE) and BI (T = 0.143; P = 0.886). These findings suggest that different age groups have varying priorities and considerations for the ease of use of technology. Social Influence on BI was significantly moderated by age (T = 2,370; P = 0.018). Age is a factor that strengthens the relationship between social influence and the conversion of intentions into real behaviors in the use of technology.

Conclusion

Based on the results of the study on "The Application of the UTAUT 3 Model to Predict EMR Acceptance by Nurses at Graha Bunda Hospital", most of the variables in the UTAUT3 model such as *performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, leadership and management, regulation and policy, technology readiness, and security & privacy were* proven to have a significant effect on *behavioral intention*.and *use behavior.* In addition, demographic factors such as age, work experience, and voluntariness of use also play a role as moderators in some relationships between variables, although not all of them show significant influences.

The success of EMR implementation is greatly influenced by the perception of benefits, ease of use, managerial support, and readiness of available technology. Therefore, strategies to increase the adoption of information technology in hospitals, especially EMR, should be focused on: (1) increasing the perception of the benefits of technology (performance expectancy), (2) simplifying interfaces and workflows (effort expectancy), (3) building positive social influence through the role of leadership or peer influence, and (4) providing adequate supporting facilities such as periodic training and reliable digital infrastructure.

For further research, it is recommended that a mixed methods approach be carried out to explore more deeply non-technical factors, such as organizational cultural values or resistance to change. In addition, testing the UTAUT3 model in hospitals of different types or locations is also important to expand the generalization of the results of this study.

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