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Effects of the technology acceptance model on attitude and behavioral intention: Evidence from physicians in secondary-level hospitals on Java Island

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Abstract

This study investigates the factors influencing doctors' adoption of Electronic Medical Records (EMR) in secondary-level hospitals in Java, Indonesia. Drawing on the Technology Acceptance Model (TAM) and Resource-Based Theory (RBT), the research examines how perceived usefulness, perceived ease of use, technology self-efficacy, outcome expectation, and discomfort shape doctors' attitudes, behavioral intentions, and actual EMR use. A causal research design was employed, surveying 400 doctors from 80 secondary-level hospitals. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypothesized relationships. The findings reveal that TAM significantly predicts doctors' attitudes and behavioral intentions, which in turn strongly influence actual system use. Conversely, moderating factors such as technology self-efficacy and outcome expectation did not significantly impact adoption, while initial discomfort did not hinder engagement, suggesting adaptive coping among physicians. The study concludes that perceptions of system usefulness and ease of use are the primary drivers of EMR adoption, overshadowing individual confidence or anticipated benefits. Practically, the results highlight the importance of user-friendly system design, hands-on training, and supportive institutional culture to enhance adoption. These insights offer actionable guidance for hospital administrators and policymakers aiming to improve digital transformation and operational efficiency in healthcare.

Keywords: Behavioral intention, Electronic medical records, Secondary-level hospitals, Technology acceptance model, Technology self-efficacy.

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1. Introduction

The implementation of Electronic Medical Records (EMR) has become a national priority in Indonesia's ongoing efforts to improve the efficiency and quality of healthcare services. Recognizing digital transformation as an essential step toward better health system governance, the Ministry of Health has launched several strategic initiatives, including the One Health Data program in 2021, which seeks to integrate health information systems across hospitals, community health centers, and clinics. The program aims to create a unified and interoperable data ecosystem that enables accurate, accessible, and secure patient information management for all stakeholders within the healthcare system.

A strong regulatory framework supports this digital transition. Laws such as the Hospital Law No. 44/2009, the Health Law No. 17/2023, and the Minister of Health Regulation No. 24/2022 mandate that all healthcare facilities adopt EMR by December 2023. The Electronic Information and Transactions Law No. 11/2008 and the Ministerial Regulation No. 269/MENKES/PER/III/2008 further emphasize that medical records must be clear, complete, and accessible in electronic format. Despite this policy support, the actual implementation of EMR has faced substantial challenges. According to the Indonesian Hospital Association [1] only 50% of hospitals have adopted EMR systems, and merely 16% manage them effectively. These numbers highlight persistent difficulties related to technological infrastructure, limited digital skills, and resistance to change among healthcare workers [2].

Existing studies show mixed perceptions among healthcare professionals. While many acknowledge that EMR improves data accuracy and coordination, others perceive it as disruptive to workflow and communication with patients [3]. Common barriers include a lack of technical expertise, insufficient training, and system designs that are not aligned with clinical routines. In response, the Ministry of Health continues to provide training, standardization, and enhanced data security protocols to support digital readiness across healthcare facilities [3-5].

Recent research grounded in the Technology Acceptance Model (TAM) provides valuable insights into the psychological and behavioral factors influencing EMR adoption. Studies consistently confirm that perceived usefulness and perceived ease of use significantly shape users' attitudes and intentions toward technology [6, 7]. Extensions of TAM, such as the Technology Readiness and Acceptance Model (TRAM), further emphasize the role of innovativeness and technology readiness in strengthening adoption behavior [8]. At the organizational level, readiness and culture have been identified as key determinants of EMR implementation success [9]. However, despite the growing body of evidence, limited research has examined these dynamics in resource-constrained environments such as Indonesia's secondary-level hospitals, where digital transformation often encounters systemic and contextual barriers.

Understanding EMR adoption in these hospitals requires an integrative perspective that goes beyond classical TAM constructs. Psychological factors such as technology self-efficacy and discomfort are increasingly recognized as pivotal in shaping individual responses to new technology. High self-efficacy enhances users' confidence and willingness to engage with EMR systems [10, 11] while discomfort stemming from poorly designed interfaces or workflow disruptions can significantly reduce perceived ease of use and acceptance [12, 13]. Simultaneously, the Resource-Based Theory (RBT) offers a complementary lens by underscoring that the capability to leverage human and technological resources constitutes a strategic advantage, particularly in healthcare institutions with limited capacity and budget.

Despite extensive use of TAM in healthcare research, several knowledge gaps remain. Theoretically, classical TAM focuses narrowly on usefulness and ease of use, leaving psychological and organizational dimensions underexplored. Contextually, prior studies have predominantly investigated large urban hospitals, overlooking smaller institutions where EMR adoption faces unique infrastructural and operational constraints [1, 2]. Methodologically, few studies have combined TAM with RBT to capture the interaction between individual attitudes and organizational capabilities that underpin successful digital transformation. Addressing these gaps is essential to advance both the theoretical understanding and practical implementation of EMR in developing healthcare systems.

Building on these foundations, this study develops an integrative framework combining TAM and RBT to examine how perceived usefulness, perceived ease of use, technology self-efficacy, discomfort, and outcome expectation collectively influence physicians' attitudes, behavioral intentions, and actual use of EMR in secondary-level hospitals. By exploring these interrelationships, the research aims to provide empirical evidence that deepens theoretical insight while offering actionable implications for policymakers and hospital leaders seeking to strengthen digital adoption in Indonesia's healthcare sector. Ultimately, the study aspires to contribute to a more efficient, equitable, and patient-centered health system through effective EMR implementation.

2. Literature Review

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis [14] provides a parsimonious framework for explaining how individuals accept and use technology through two key beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Later refinement by Davis [14] established that ease of use enhances perceived usefulness, positioning TAM as a cornerstone in technology adoption research. Subsequent developments TAM2 [15] and TAM3 [16] incorporated social, contextual, and psychological factors, such as subjective norms, job relevance, computer self-efficacy, and anxiety, thus expanding the model's explanatory depth. Over time, TAM has been validated across diverse sectors. In healthcare, it effectively predicts the adoption of electronic medical records [17] while in smart city contexts, extensions including Perceived Security and Compatibility have improved its contextual relevance [18]. Despite numerous modifications, recent studies reaffirm that PU and PEOU remain the most powerful predictors of technology acceptance [7]. This enduring flexibility underscores TAM's relevance in understanding digital transformation within healthcare organizations, particularly secondary-level hospitals in emerging economies.

2.2. Technology Self-Efficacy

The concept of Technology Self-Efficacy (TSE) has evolved significantly alongside technological advancement and digital transformation. Originating from Compeau and Higgins [19] as computer self-efficacy, it described individuals' confidence in using computers to perform specific tasks. Later, Zeldin and Pajares [20] enriched the construct by highlighting the influence of social and emotional factors, such as vicarious experience and verbal persuasion in shaping self-belief in technology use. Moving toward an organizational perspective, Straub [21] demonstrated that employees' confidence in using technology critically determines the success of information system adoption, marking a shift from individual to institutional contexts. In subsequent years, TSE gained broader relevance across diverse domains. During the pandemic, Pan [22] identified TSE as a key factor driving engagement and adaptability in online learning, while Saville and Foster [23] emphasized its role as a psychological resource for resilience in hybrid, technology-driven workplaces. Recent studies have further deepened its theoretical integration, Xu, et al. [24] embedded TSE into the Technology Acceptance Model (TAM), showing its direct influence on perceived ease of use, perceived usefulness, and technology adoption intention. In healthcare, Andarwati, et al. [25] confirmed that health workers with higher TSE exhibit greater readiness and enthusiasm in using hospital information systems, improving efficiency and service quality. Collectively, these developments position Technology Self-Efficacy as a critical foundation for understanding human readiness, confidence, and adaptability in the digital era.

2.3. Attitude

The theory of attitude has evolved from a simple psychological response to a multidimensional construct central to understanding human behavior in technological contexts. Initially introduced by Spencer [26] as a mental state influenced by thought, emotion, and social environment, the concept was later refined by Hill, et al. [27] through the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), which linked attitudes to intention and behavior. Subsequent scholars, including Baron and Byrne [28]; Icek [29] and Kreitner, et al. [30] emphasized attitude's cognitive, affective, and behavioral dimensions, highlighting its role in shaping individual responses to both social and technological stimuli. Empirical evidence further supports its predictive power in technology adoption by Hu, et al. [31]; Abramson, et al. [32] and Bordalba and Bochaca [33] demonstrated that positive attitudes accelerate adoption and enhance satisfaction, while Bhatt and Shiva [34] and Yu, et al. [35] expanded its relevance to digital innovation and social interaction. Overall, attitude remains a fundamental determinant of technology acceptance, reflecting the interplay between cognition, emotion, and behavior in the era of digital transformation.

2.4. Behavioral Intention

The concept of behavioral intention originates from social psychology and serves as a central predictor of human behavior. Davis [14] through the Technology Acceptance Model (TAM), first positioned behavioral intention as a key determinant of technology usage, shaped by perceived usefulness and perceived ease of use. Ajzen [36] later expanded its theoretical scope through the Theory of Planned Behavior (TPB), identifying attitude, subjective norm, and perceived behavioral control as its primary antecedents. Building on these foundations, Venkatesh, et al. [37] integrated major acceptance models into the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlights performance expectancy, effort expectancy, social influence, and facilitating conditions as core predictors of behavioral intention. Beyond technology, the construct has been widely applied in consumer behavior research, Namkung and Jang [38] and Peter and Olson [39] linked it to repurchase intention and brand loyalty, while Saha and Theingi [40] and Purwianti and Tio [41] emphasized its role in fostering customer retention and positive word of mouth. More recent studies, such as Yazdanpanah, et al. [42]; Nguyen [43] and Kim and Park [44] extended the framework by incorporating social and situational factors, illustrating that behavioral intention reflects a dynamic interaction of personal belief, social influence, and contextual conditions. Overall, behavioral intention has evolved from a theoretical construct into a multidimensional concept widely applied to explain technology adoption, consumer loyalty, and digital engagement in modern contexts.

2.5. Outcomes Expectation

The concept of *outcomes expectation* has evolved from early cognitive theories to contemporary applications in technology and behavioral research. Tolman [45] latent learning theory and refined through motivational [46] and attributional frameworks [47] it explains how individuals form beliefs about future results based on experience and perceived control. *Social Cognitive Theory* further established *self-efficacy* as a central determinant of positive expectations and subsequent actions [20]. Recent studies extend this concept to digital and AI contexts, showing that perceived benefits, trust, and technological efficacy strongly shape adoption and user behavior [48].

2.6. Actual Use

The concept of *actual use* refers to the extent and manner in which users engage with a technology in real-life settings, representing the observable behavior that follows the intention to use. Early studies emphasized that *actual use* reflects not only quantitative aspects such as frequency or duration but also qualitative perceptions of usefulness and productivity improvement [49]. Further conceptualized it through three indicators like actual behavior, usage frequency, and user satisfaction offering a structured framework for its measurement [50]. Subsequent studies reinforced that *actual use* differs from *behavioral intention* as it captures what users genuinely do rather than what they plan to do [51, 52]. More recently, Kim, et al. [53] extended its application to digital and online environments, highlighting *actual use* as a crucial measure for evaluating post-adoption engagement, system effectiveness, and user-centered technological improvement. Overall, the construct has evolved from perceptual to behavioral emphasis, underscoring its vital role in assessing the success and sustainability of technology adoption.

2.7. Discomfort

The concept of *discomfort* describes an individual's feelings of unease, anxiety, or lack of confidence when interacting with new technologies [54]. As a key dimension of the Technology Readiness Index (TRI), it reflects psychological barriers arising from perceived lack of skills or fear of making mistakes. Later works highlight that *discomfort* is linked to perceived loss of control and can be reduced through user support and system simplification [55, 56]. Recent studies emphasize its multidimensional nature, shaped by personal experience, digital literacy, and social context [13, 57]. Thus, *discomfort* serves as a crucial determinant of technology readiness and adoption, guiding user-centered design and training interventions.

3. Hypothesis Development

3.1. TAM and Attitude

Technology Acceptance Model (TAM) explains how perceived usefulness and perceived ease of use shape users' attitudes toward technology. In secondary-level hospitals, when doctors perceive Electronic Medical Records (EMR) as beneficial and easy to use, they develop more positive attitudes toward the system [35, 58, 59]. Positive attitudes enhance acceptance and effective use of EMR, improving operational efficiency and service quality.

$H_{1:}$ Higher TAM among doctors leads to more positive attitudes toward hospital system use.

3.2. TAM and Behavioral Intention

Behavioral intention reflects the willingness to adopt and use technology. TAM components perceived usefulness and ease of use significantly influence doctors' intentions to use EMR [51, 58-63]. Stronger perceptions of TAM foster greater willingness to engage with digital systems.

$H_{2:}$ Higher TAM among doctors increases their behavioral intention to use hospital systems.

3.3. Attitude and Behavioral Intention

Attitude acts as a key predictor of behavioral intention. Doctors with positive attitudes toward EMR are more likely to adopt and integrate it into daily practice [58, 61, 64-66]. Positive attitudes thus facilitate smoother technology adoption.

$H_{3:}$ More positive attitudes enhance doctors' behavioral intention to use hospital systems.

3.4. Technology Self-Efficacy, TAM, and Attitude

Technology self-efficacy is the confidence in one's ability to use technology affects perceived usefulness and ease of use [67-69]. Higher self-efficacy promotes positive attitudes and readiness to adopt EMR in secondary-level hospitals.

$H_{4:}$ Higher technology self-efficacy increases TAM and doctors' positive attitudes toward system use.

3.5. Technology Self-Efficacy, TAM, and Behavioral Intention

Self-efficacy also drives behavioral intention through TAM components. Doctors confident in using EMR perceive it as beneficial and user-friendly, leading to stronger intentions to use it consistently [44, 70, 71].

$H_{5:}$ Higher technology self-efficacy increases TAM and doctors' behavioral intention toward hospital systems.

3.6. Outcomes Expectation, Attitude, and Behavioral Intention

Outcomes expectation, the belief that technology improves work efficiency and quality shapes both attitude and behavioral intention [72-75]. Doctors who expect positive results are more motivated to adopt EMR and form favorable attitudes.

$H_{6:}$ Higher outcomes expectation enhances doctors' attitude and behavioral intention toward system use.

3.7. Behavioral Intention and Actual Use

Behavioral intention predicts actual technology use. Stronger intentions lead to more frequent and consistent EMR usage, improving operational performance [58, 62, 76].

$H_{7:}$ Higher behavioral intention results in higher actual use of hospital systems.

3.8. Discomfort and TAM

Discomfort feelings of being overwhelmed or lacking control negatively affects TAM components [12, 13, 54, 77, 78]. Doctors experiencing high discomfort are less likely to perceive EMR as useful or easy to use, reducing adoption likelihood.

$H_{8:}$ Discomfort negatively affects doctors' TAM toward hospital systems.

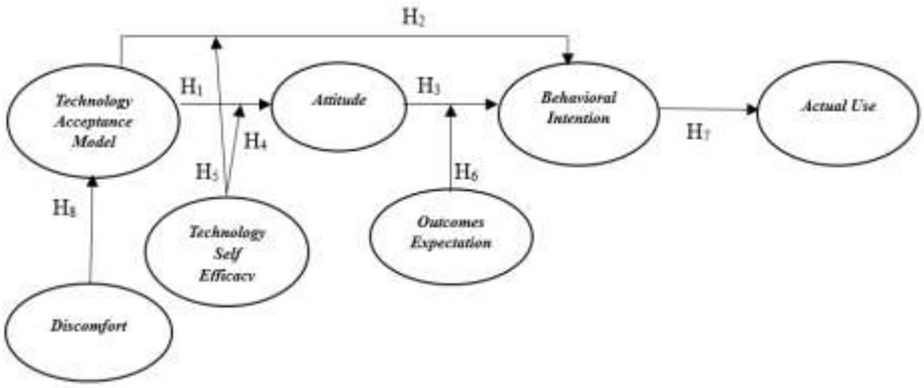

Figure 1.
Research Model.

4. Methodology

This study employs a causal research design to examine the cause-and-effect relationships among key variables, focusing on whether changes in independent variables lead to changes in dependent variables rather than merely identifying correlations [79, 80]. The research model integrates validated theoretical frameworks, including the Technology Acceptance Model (TAM) measured using Chong, et al. [60] with perceived usefulness and perceived ease of use dimensions, Technology Self-Efficacy based on Xu, et al. [24]. Attitude following [35]. Behavioral Intention adapted from Sepasgozar, et al. [18]. Outcomes Expectation from Mubarak, et al. [48]. Actual Use using Li [81] and Discomfort measured with Kampa [77]. All constructs were operationalized using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The population comprises doctors working in secondary-level hospitals in Java, Indonesia, members of the Indonesian Hospital Association (PERSI), who are primary users of Electronic Medical Records (EMR) and play a crucial role in clinical decision-making. Based on SEM-PLS guidelines, with eight structural paths in the model, a minimum of 80 hospitals was required, with five doctors per hospital, resulting in a target sample of 400 doctors from 80 hospitals. Data collection was conducted through direct visits in March 2025.

The instrument development process involved systematic drafting of questionnaires based on theoretical constructs, followed by a pilot test with 30 doctors from six secondary-level hospitals to evaluate clarity, relevance, and reliability. Pilot data were analyzed using Exploratory Factor Analysis (EFA) in IBM SPSS 25 to assess construct validity and Cronbach's Alpha to determine internal consistency. Items showing low validity or reliability were revised to ensure robust measurement.

Hypotheses were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM), which allowed simultaneous analysis of complex relationships among variables. Path coefficients and t-values were examined to assess statistical significance at $t \geq 1.96$ and $p \leq 0.05$, while R-squared values measured the explanatory power of the model. In addition, Analysis of Variance (ANOVA) was conducted to identify significant differences among doctors based on demographic characteristics and hospital performance data from the Ministry of Health, providing contextual insights and external validation of the findings.

Ethical considerations were strictly observed, including voluntary participation, confidentiality, and clear explanations of the study objectives to respondents. Through this methodological approach, the study ensures valid and reliable measurement, controlled bias, and a comprehensive understanding of the factors influencing doctors' attitudes, intentions, and actual use of EMR in secondary-level hospitals, offering a solid empirical foundation for practical recommendations such as targeted training, technical support, and operational policies aligned with hospital performance.

5. Results and Discussion

At the initial stage of this study, descriptive analysis was conducted to provide an overview of the respondents' characteristics and the distribution of the research variables. Data were collected through an online questionnaire distributed via Google Form to potential respondents who met the inclusion criteria, namely physicians working in secondary level hospitals in Java Island, affiliated with the Indonesian Hospital Association (PERSI), with a minimum of two years of work experience, and actively using Electronic Medical Record (EMR) systems. A total of 400 responses were obtained, fulfilling the sample requirements for this study. Demographic data, including gender, age, highest education level, work experience, and hospital location, were collected to ensure the representativeness of physicians in secondary level hospitals across Java. The analysis revealed that the majority of respondents were female (75%), with male respondents comprising 25%. Regarding hospital location, most respondents were from Banten (53%), followed by Central Java (15%), West Java (11%), Jakarta (9%), and East Java and Yogyakarta (6% each). The age distribution ranged from 25 to 50 years, with a predominance in the 30–40-year group, and all respondents held at least a bachelor's degree in medicine with clinical specialization.

Descriptive statistics such as mean, standard deviation, and minimum and maximum values were computed for the main study variables, including Technology Acceptance Model (TAM) constructs (Perceived Ease of Use and Perceived Usefulness), Technology Self-Efficacy, Outcomes Expectation, Attitude, Behavioral Intention, Actual Use, and

Discomfort. This preliminary analysis was aimed at assessing data quality and ensuring no anomalies or invalid responses before proceeding to more complex statistical testing. Gender-based ANOVA results indicated significant differences for Attitude, Behavioral Intention, Outcomes Expectation, Actual Use, and Discomfort, while TAM and Technology Self-Efficacy did not differ significantly. Age, education, and work experience did not yield significant differences across any variables, whereas hospital location influenced Technology Self-Efficacy, Outcomes Expectation, and Actual Use. Levene's test confirmed that variances were generally homogeneous, with a few exceptions.

The overall descriptive analysis indicated that respondents exhibited positive perceptions across all variables, with mean scores ranging from 5.955 to 6.210. TAM had the highest mean (6.210, SD = 0.838), reflecting high and relatively uniform acceptance of technology, followed by Actual Use (6.122, SD = 1.211) and Behavioral Intention (6.110, SD = 1.189). Attitude (6.074, SD = 1.306) and Technology Self-Efficacy (6.063, SD = 1.272) showed positive perceptions but with moderate variance, whereas Discomfort had the lowest mean (5.955, SD = 1.113), indicating a notable but manageable level of user discomfort.

Hypothesis testing employed Structural Equation Modeling (SEM) using SmartPLS 4, with prior assessment of measurement model validity and reliability through factor loadings, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha. All indicators demonstrated strong convergent validity (outer loadings ≥ 0.70, AVE ≥ 0.50) and internal consistency (CR and Cronbach's Alpha ≥ 0.70). Discriminant validity assessed via the Fornell-Larcker criterion confirmed that each construct was empirically distinct. Collinearity statistics (VIF) ranged from 1.000 to 2.173, indicating no multicollinearity issues. Model fit indices showed an SRMR of 0.042 for the saturated model but 0.190 for the estimated model, while NFI values were slightly below the recommended threshold, consistent with PLS-SEM's predictive-focused evaluation approach.

Structural model evaluation revealed mostly positive path coefficients. TAM significantly influenced Attitude ($\beta = 0.375$, $p < 0.001$) and Behavioral Intention ($\beta = 0.188$, $p = 0.003$), while Attitude positively affected Behavioral Intention ($\beta = 0.145$, $p = 0.001$). Outcomes Expectation and Behavioral Intention also significantly influenced Behavioral Intention ($\beta = 0.236$, $p = 0.001$) and Actual Use ($\beta = 0.432$, $p < 0.001$), respectively. Discomfort had a substantial effect on TAM ($\beta = 0.509$, $p < 0.001$). Interaction terms involving Technology Self-Efficacy yielded weaker or non-significant effects. The R^2 values for Attitude (0.223) and Actual Use (0.187) were low, while Behavioral Intention (0.329) and TAM (0.259) were moderate, indicating the model explained limited to moderate variance in endogenous constructs. Effect size analysis (f^2) highlighted the strongest impact of Discomfort on TAM ($f^2 = 0.349$, medium), followed by Behavioral Intention on Actual Use ($f^2 = 0.230$, medium), with other relationships showing small or negligible effects.

The results of this study shed light on how doctors in secondary level hospitals engage with hospital information systems. The supported hypotheses, H1, H2, H3, and H7, illustrate a clear pathway from perception to behavior. Specifically, higher levels of Technology Acceptance Model (TAM) among doctors positively influence their attitude toward using the system (H1), which in turn strengthens their behavioral intention (H3), and ultimately drives actual system use (H7). Additionally, TAM also has a direct effect on behavioral intention (H2), confirming that doctors' perceptions of the system's usefulness and ease of use are critical in shaping their readiness to adopt it. Collectively, these findings reaffirm the central premise of TAM: perceptions shape attitude, attitude guides intention, and intention determines actual behavior.

On the other hand, the moderating role of Technology Self-Efficacy (TSE) in H4 and H5 was not supported. Contrary to expectations, higher TSE did not significantly enhance the effect of TAM on either attitude or behavioral intention. This suggests that doctors' confidence in their technological abilities may already be sufficiently high or relatively uniform, making self-efficacy less influential. It also points to the potential importance of contextual or organizational factors such as training, peer support, or institutional policies, over individual capability in driving system adoption.

Similarly, Outcomes Expectation (OE) did not show the anticipated positive effect on attitude and behavioral intention (H6). This indicates that doctors' engagement with the system is less influenced by anticipated benefits and more by their immediate perceptions of the system's practicality and ease of use. Emphasizing tangible, day-to-day advantages may therefore be more effective than highlighting long-term outcomes.

Interestingly, discomfort (H8) did not negatively affect TAM as hypothesized. The positive coefficient suggests that initial challenges or frustrations with the system may prompt adaptation, problem-solving, and persistence, ultimately supporting engagement rather than hindering it. This may reflect a professional culture where overcoming technological obstacles is expected and even valued.

Overall, these findings present a coherent and nuanced picture. While TAM remains a strong predictor of attitude, intention, and actual use, individual factors such as TSE and OE do not always operate as expected. Adoption in secondary level hospitals appears primarily driven by perception and attitude, with contextual and professional factors shaping the finer details of user behavior. For hospital administrators, the implications are clear: designing user-friendly systems, providing practical support and training, and fostering a supportive institutional environment are likely more impactful than focusing solely on individual confidence or anticipated outcomes. These insights not only reinforce the theoretical robustness of TAM in healthcare settings but also offer practical guidance for facilitating effective and sustainable technology adoption among doctors.

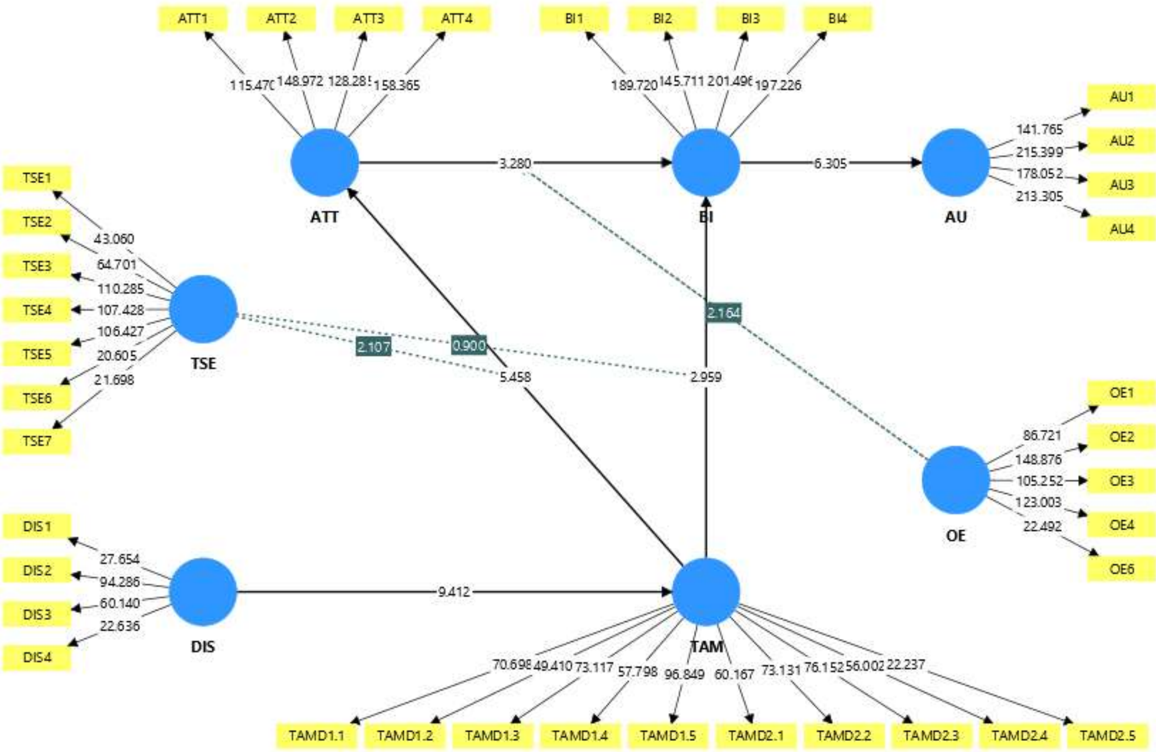

Figure 2.
Path Coefficients Diagram.

6. Conclusion

This study provides empirical evidence on the adoption of hospital information systems by doctors in secondary level hospitals. The findings confirm that the Technology Acceptance Model (TAM) effectively predicts doctors' attitudes, behavioral intentions, and actual system use. Attitude serves as a crucial mediator between perceived usefulness and behavioral intention, while behavioral intention strongly drives actual usage. Conversely, moderating factors such as Technology Self-Efficacy and Outcomes Expectation did not significantly influence the adoption process, suggesting that perceptions of system usability and practicality are more decisive than individual confidence or anticipated outcomes. The results also reveal that initial discomfort with the system does not necessarily hinder adoption, highlighting the adaptive and resilient nature of medical professionals in engaging with technology. Overall, TAM remains a robust framework for understanding and guiding digital system adoption in healthcare settings.

7. Implications

The study carries both theoretical and practical implications. Theoretically, it reinforces TAM's relevance in healthcare, particularly in secondary level hospitals, by demonstrating how perception shapes attitude and intention, leading to actual system use. Practically, hospital administrators and IT managers should prioritize user-friendly system design, hands-on training, and clear guidance to support doctors' engagement. Encouraging a supportive institutional culture where initial challenges are normalized can facilitate adoption. Additionally, these findings suggest that emphasizing immediate usability and practical benefits is more effective than solely promoting anticipated outcomes or relying on doctors' self-efficacy. Policymakers and hospital leadership can use these insights to optimize implementation strategies, maximize technology utilization, and ultimately improve operational efficiency and patient care quality.

8. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the research focuses solely on doctors in secondary level hospitals, limiting generalizability to other healthcare personnel or hospital types. Second, the study employs cross-sectional data, which restricts causal inference and does not capture adoption dynamics over time. Third, while TAM provides a strong explanatory framework, other contextual or organizational factors such as management support, workflow integration, and peer influence may also play significant roles. Future research could expand the sample to include multiple hospital levels and diverse healthcare professionals, adopt longitudinal designs to track system adoption over time, and explore additional moderating or mediating variables to provide a more comprehensive understanding of technology adoption in healthcare contexts.

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