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Adoption Intentions Toward AI-based Clinical Decision Support Tools: A Tam Study on Hospital Pharmacists

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ABSTRACT

The increasing prevalence of antibiotic resistance leads to an alarming challenge to global healthcare, necessitating the adoption of machine learning (ML)-driven clinical decision support systems (CDSS) to enhance antimicrobial stewardship. Despite its potential, hospital pharmacist's adoption of ML-based antibiotic resistance predictors remains limited due to usability, trust, organisational support, and perceived risk concerns. This study uses an extended version of Technology Acceptance Model (TAM) to examine the primary factors influencing pharmacists' behavioural intention (BI) to adopt the ML-driven CDSS. A cross-sectional survey was conducted among 235 hospital pharmacists across major provinces in Indonesia, using a PLS-SEM approach to test hypothesised relationships. The findings reveal that perceived usefulness (PU) ($\beta = 0.355$, $p < 0.001$) is the strongest predictor of BI, followed by trust in technology (TT) ($\beta = 0.179$, $p = 0.017$), social influence (SI) ($\beta = 0.184$, $p = 0.009$), and facilitating conditions (FC) ($\beta = 0.150$, $p = 0.010$). Perceived risk (PR) negatively affects BI ($\beta = -0.103$, $p = 0.023$), highlighting concerns over AI reliability. The study underlines the need for hospital administrators to enhance IT support and training, policymakers to establish AI regulatory frameworks, and professional organisations to promote AI acceptance through peer advocacy. Clinically, increased

adoption of ML-driven CDSS can improve the accuracy of antibiotic prescribing, reduce resistance rates, and enhance patient safety. It provides insights into optimising AI interventions in antimicrobial stewardship programmes and guiding future implementation strategies in hospital pharmacy practice.

Keywords: Artificial intelligence, clinical decision support system, machine learning, pharmacist adoption, technology acceptance model.

INTRODUCTION

Antibiotic resistance (ABR) is considered one of the most significant public health issues, making bacterial infections increasingly difficult to treat. The World Health Organization has identified that it could lead to up to 10 million deaths annually by 2050 without urgent intervention (Lesho & Laguio-Vila, 2019; Pulingam et al., 2022; Ch'ng, 2024). The extensive misuse and overuse of antibiotics have accelerated the emergence of resistant bacterial strains, causing increased healthcare costs, prolonged hospital stays, and higher mortality rates (Ravindranath et al., 2022; Sharma et al., 2024). In response, healthcare systems are integrating advanced technologies, e.g., Machine Learning (ML), to predict ABR patterns and support antimicrobial stewardship efforts. The ML-generated ABR predictors analyse huge datasets of microbial susceptibility patterns to optimise antibiotic selection, potentially improving clinical decision-making and minimising the spread of resistance. However, the adoption of the predictive tools remains inconsistent, particularly among hospital pharmacists, despite their critical role in antimicrobial stewardship (Lai et al., 2022; Wong et al., 2021).

Hospital pharmacists play a key role in antimicrobial stewardship programmes (ASPs) by ensuring the rational use of antibiotics, monitoring resistance patterns, and providing guidance on optimal regimens. Their acceptance and use of ML-driven ABR predictors are vital to integrating artificial intelligence (AI) into clinical workflows. However, various factors influence their adoption of such AI-driven decision-support tools. The Technology Acceptance Model (TAM) has been widely utilised to explain the adoption of new technologies in healthcare, emphasising perceived usefulness (PU) and perceived ease of use (PEOU) as key determinants of behavioural intention (BI) (S. D. Kim, 2024; Suresh et al., 2016). Although TAM provides a useful framework, ML-driven clinical tools introduce unpredictable challenges beyond PU and PEOU. Other constructs, including trust in technology (TT), social influence (SI), facilitating conditions (FC), and perceived risk (PR), may significantly affect pharmacists' willingness to adopt ML-based ABR predictors. Since pharmacists work in highly structured healthcare environments, external influences from peers, hospital policies, and regulatory bodies may also shape their perceptions of ML tools (Zhang et al., 2024).

Despite the growing body of research on AI adoption in healthcare, limited attention has been given to hospital pharmacists, although they are integral to ASPs. Most studies underline physicians and general AI application in clinical settings, leaving the pharmacist's adoption behaviours (Barański, 2024; Hu et al., 2022; Mashabab et al., 2024). The pharmacist's perspectives on AI-driven decision-support tools remain underexplored, and understanding factors influencing their BI is very crucial for confirming the successful application of ABR predictors. Moreover, while TAM has been extensively utilised to study healthcare professionals' technology adoption, few studies have empirically validated the impact of TT and PR on the pharmacists' decision-making (Ferawaty et al., 2024; Ma, 2021). The integration of ML into antimicrobial stewardship needs a deeper understanding of how these factors influence pharmacists' willingness to adopt AI-driven tools.

Understanding the pharmacists' adoption of ML-generated decision-support tools is critical due to their role as hospital medication experts. Unlike other healthcare professionals, pharmacists are responsible for evaluating antibiotic regimens, assessing drug interactions, and ensuring the appropriate use of antibiotics. Their perspective on AI-driven predictions may differ significantly from that of physicians since their primary concern revolves around the reliability and accuracy of drug-related recommendations. Additionally, they must comply with the institutional guidelines, making FC a key determinant in their willingness to adopt the tools into their practice (Ajmal et al., 2025). A lack of TT concerns about the interpretability of ML-generated recommendations and a high PR of errors could significantly inhibit adoption. The absence of studies addressing these concerns presents a significant research gap, making it imperative to explore an extended TAM that covers trust, risk perception, and institutional support (Hu et al., 2019; Nikolic et al., 2024; Sleiman et al., 2021).

Hospitals worldwide are under increasing pressure to apply AI-driven solutions to address AMR. With multi-drug-resistant (MDR) infections on the rise, the need for ML-supported tools to improve antibiotic prescribing has never been more urgent. However, the effectiveness of these tools remains limited without pharmacists' adoption. A delayed transition to the AI-based clinical decision-making resulted in a continued reliance on outdated antibiograms and empirical antibiotic selection, worsening resistance rates (Miano et al., 2012). Given the urgent need to integrate ML-driven decision-support systems, this study primarily aims to provide evidence-based insights into the factors influencing pharmacists' BI to adopt these AI-driven tools.

LITERATURE REVIEW

Technology Acceptance Model

Technology Acceptance Model (TAM), originally introduced by Davis in 1989, has been a basic framework in understanding user acceptance of information systems (Davis, 1989). It hypothesised that two constructs – PU and PEOU– significantly influence the individual's intention to use a technology or system (Weerasinghe & Hindagolla, 2017). PU is the degree to which a person believes that using a particular system would enhance their job performance (Baby & Kannammal, 2020), while PEOU refers to the extent to which a person believes using the system would be effort-free. These constructs are theorised to directly affect the user's attitudes toward technology, influencing their behavioural intentions and actual system use (Attié & Meyer-Waarden, 2022).

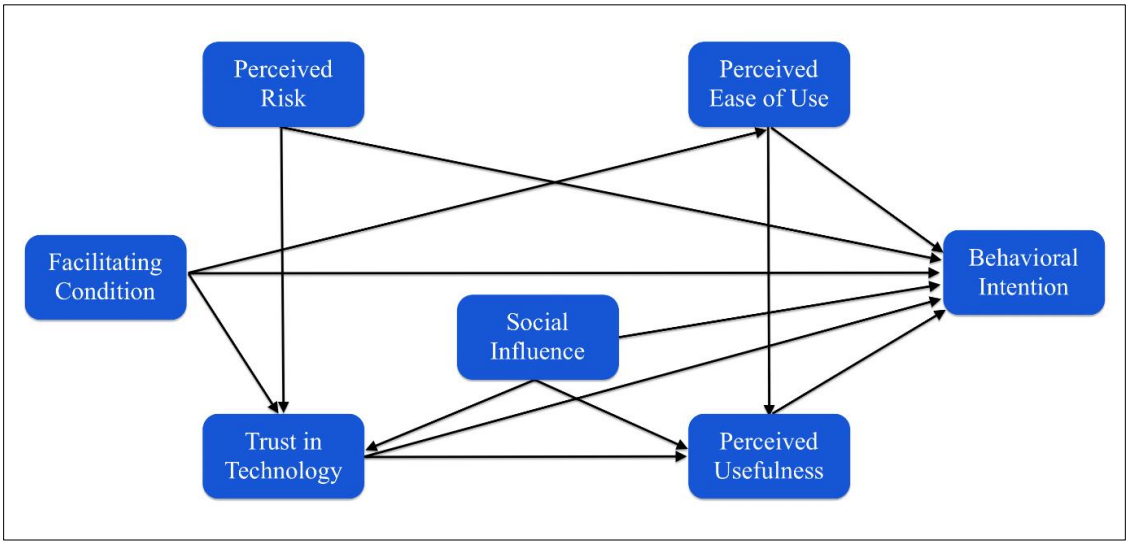
Over the years, TAM has been extensively implemented and validated across various domains, including healthcare. In the context of health informatics, it has been utilised to assess the acceptance of electronic health records (EHRs), telemedicine, and other digital tools. For instance, a systematic review highlighted that PU and PEOU are critical determinants in clinicians and patients alike' adoption of health information systems (HIS) (Rahimi et al., 2018). The model's simplicity and predictive power contributed to its widespread adoption; however, it has also faced criticism for its limitations. A limitation of the original TAM is its exclusion of external variables that may influence technology acceptance (Malatji et al., 2020). The basic model does not account for various factors, such as social influence, facilitating conditions, and individual differences. This gap has led to the development of extended versions of TAM, aiming to involve a broader range of determinants to better explain user behaviour in complex environments like healthcare.

Extended TAM for AI and Healthcare Technologies

Researchers have proposed extensions to TAM by integrating additional constructs relevant to the healthcare context to address the limitations of the original model. These extended models aim to capture the multifaceted nature of technology adoption in clinical settings, especially concerning advanced systems like AI applications. One such extension involves the inclusion of TT factors, which recognises that healthcare professionals' confidence in the reliability and accuracy of AI systems is important for adoption. A study evaluated the acceptance of clinical decision support tools using an integrated TAM and found that trust significantly influenced physician's intentions to use AI-based recommendations (Panigutti et al., 2022). Similarly, PR has been identified as a critical factor, covering concerns about the data privacy, security, and potential negative consequences of technology use (Zhu et al., 2014). An interview study noted that PR influenced healthcare professionals to adopt AI tools, underlining the need to address the apprehensions in implementation strategies (Siira et al., 2024). Figure 1 illustrates the structure of the extended TAM utilised in this study.

Figure 1

The Structure of the Extended Technology Acceptance Model (TAM) of the Study



Based on the framework, the following hypotheses are proposed:

- H1: PU has a positive influence on BI.
- H2: PEOU has a positive influence on PU.
- H3: PEOU has a positive influence on BI.
- H4: SI has a positive influence on BI.
- H5: TT has a positive influence on PU.
- H6: TT has a positive influence on BI.
- H7: FC have a positive influence on BI.
- H8: FC have a positive influence on PEOU.
- H9: PR has a negative influence on BI.
- H10: PR has a negative influence on TT.
- H11: SI has a positive influence on TT.
- H12: SI has a positive influence on PU.
- H13: FC have a positive influence on TT.

Key Factors Affecting Behavioural Intention

In the context of hospital pharmacists' adoption of ML-driven ABR predictors, some factors have been identified as influential in shaping BI constructs:

- PU is still becoming a central determinant in technology acceptance. The perceived benefits of ML-driven tools in enhancing clinical decision-making are essential for hospital pharmacists. If pharmacists believe that such predictors can improve accuracy in antibiotic selection and patient outcomes, they are more likely to adopt them. A study on AI implementation in UAE healthcare settings found that PU significantly predicted healthcare professionals' intention to use AI applications (Mansour & Bick, 2024).
- PEOU defines the user-friendliness of ML tools as critical for adoption. Pharmacists are more inclined to use intuitive information systems that require minimal effort to learn. Complex interfaces or cumbersome workflows can act as barriers. Positive research highlighted that ease of use significantly influences the acceptance of health information systems, suggesting that adequate training and system design are vital for facilitating adoption (Walle et al., 2023).
- SI describes that perceptions and attitudes of colleagues, supervisors, and the professional community can influence an individuals' decision to adopt a new technology. In a study examining technology acceptance among healthcare providers, it was found that SI played a vital role in shaping attitudes toward new systems, indicating that endorsement from respected peers and leaders can encourage adoption (Akinwale & Kyari, 2022; Cioc et al., 2023).
- TT defines trust as the reliability and accuracy of ML algorithms as essential. Pharmacists need to have confidence that the predictions made by these tools are based on robust data and can be relied upon in clinical decision-making. A good study discovered clinician acceptance of AI-based treatment recommendations and found that trust was a significant factor influencing the utilisation of AI tools in healthcare settings (Sivaraman et al., 2023).
- FC describes that the availability of resources, including technical support, training programmes, and necessary infrastructure, can influence the adoption of ML tools. An environment that supports the required assistance and resources can help improve pharmacists' willingness to adopt new systems into their practice. A systematic review indicated that FC was a primary determinant of healthcare professional's acceptance of clinical decision support systems (Kilsdonk et al., 2011).
- PR defines that concerns about potential adverse outcomes, e.g., errors in predictions, ethical issues, and legal implications, can inhibit pharmacists from adopting ML-driven technologies. Addressing the concerns through clear guidelines, accountability frameworks, and robust system validation can minimise perceived risks. It is underlined that PR, i.e., data security and patient safety concerns, were barriers to the acceptance of AI in healthcare (Ghozali & Murni, 2023; Murphy, 2024).

MATERIAL AND METHODS

Research Design

This study used a cross-sectional survey design to assess factors influencing hospital pharmacists' behavioural intentions to adopt ML-driven ABR predictors. The survey design was selected due to its efficacy in describing the current attitudes and intentions within a specific population at a single point

in time, thereby providing a comprehensive overview of the factors under analysis (J. H. Kim, 2023). Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyse complex relationships between multiple latent constructs inherent in TAM. It is especially beneficial in exploratory research contexts where the primary objective is theory development and prediction (Hair & Alamer, 2022). It is well-suited for handling complex models with numerous indicators and constructs, notably when data did not meet the stringent assumptions of covariance-based SEM, including multivariate normality and large sample sizes. It aligns with recent healthcare technology adoption research applications, where PLS-SEM has been effectively employed to evaluate user acceptance and behavioural intentions toward new systems (Magno et al., 2024). Such an analytical process was performed utilising SmartPLS version 3.2.9, facilitating measurement and structural model assessments.

Data Collection

Data was collected through an online survey between March and May 2024. The online method was chosen because of its efficiency in reaching a geographically dispersed population and its practicality when in-person collection may be relatively challenging (Wu et al., 2022). The online survey was disseminated via multiple channels, including professional organisations and social media such as WhatsApp, Facebook, Instagram, and LinkedIn. The platforms were selected based on their widespread use among professionals in Indonesia, allowing effective communication and engagement. Furthermore, to encourage participation, initial invitations were sent through the official channels of pharmacy associations, followed by reminders to maximise response rates. Participation was voluntary, and informed consent was obtained from all the respondents before survey completion. This survey was particularly designed to be concise, requiring approximately 15–20 minutes to complete, to avoid respondent burden and enhance completion rates.

Measurement of Variables

Instrument Development

The instrument of this study, as shown in Table 1, was developed based on the established scales from the TAM and its extensions, tailored to the context of ML-driven ABR predictors. It mainly consisted of multiple items measuring seven key constructs, e.g., PU, PEOU, BI, TT, FC, SI, and PR. Each was measured using a minimum of three items to confirm adequate coverage of the construct domain and improve the measurements' reliability. Meanwhile, a 4-point Likert scale was used for all the items, with response options ranging from 1 (Strongly Disagree) to 4 (Strongly Agree). The decision to utilise a 4-point scale intentionally eliminated a neutral midpoint, therefore encouraging respondents to express a definitive stance on each statement. It is supported by research suggesting that the absence of a neutral option leads to more discriminative responses and reduces social desirability bias (Suzer-Gurtekin, 2024).

Pre-Testing and Validation

Before full-scale deployment, the instrument underwent a pre-testing phase involving a small sample of hospital pharmacists (n=15) who were not part of the main study sample. They were asked to complete the survey and provide feedback on item clarity, relevance, and overall comprehensibility. Based on the feedback, minor revisions were made to the wording of specific items to enhance clarity and ensure cultural appropriateness. This phase helped to identify and rectify potential issues related to item interpretation and survey navigation, improving the quality of the data collected in the study.

Table 1

Question Items of the Extended Technology Acceptance Model (TAM)

Construct	Item	Question Items
BI	BI1	I intend to use the predictor in my clinical decision-making.
	BI2	I will use the predictor regularly in my professional practice.
	BI3	I plan to recommend the predictor to my colleagues.
	BI4	I am likely to adopt the predictor when available.
FC	FC1	My hospital provides sufficient resources to support the use of predictor.
	FC2	Technical support is available when I face difficulties using the predictor.
	FC3	There is adequate training available for pharmacists on using the predictor.
	FC4	My workplace environment supports the integration of the predictor.
PEOU	PEOU1	Learning how to use the predictor would be easy for me.
	PEOU2	I find the predictor easy to use in my daily workflow.
	PEOU3	My interaction with the predictor is clear and understandable.
	PEOU4	It would be easy for me to become skillful at using the predictor.
PU	PU1	Using the predictor would enhance ability to select appropriate antibiotics.
	PU2	The predictor would improve my efficiency in antibiotic stewardship.
	PU3	The predictor would help me make better clinical decisions.
	PU4	The predictor would be beneficial in reducing antibiotic resistance cases.
PR	PR1	I am concerned that the predictor may provide inaccurate predictions.
	PR2	Using the predictor could lead to incorrect antibiotic prescriptions.
	PR3	I worried on the potential ethical and legal implications of the predictor.
	PR4	I perceive a risk in fully depending on the predictor for decision-making.
SI	SI1	My colleagues think I should use the predictor in my practice.
	SI2	My hospital management supports the adoption of the predictor.
	SI3	Leading professionals in my field recommend the use of the Predictor.
	SI4	The adoption of the predictor is becoming a standard in my profession.
(TT)	TT1	I trust the predictor to provide reliable recommendations.
	TT2	The predictions made by the predictor are scientifically valid.
	TT3	I believe that the predictor is unbiased in its recommendations.
	TT4	The predictor operates with high accuracy and reliability.

Data Analysis

Descriptive Statistics

Descriptive statistical analyses were performed to summarise the respondents' demographic characteristics and provide an overview of their responses to the survey items. Measures of central tendency (mean) and variability (standard deviation) were calculated for each construct item, and

frequency distributions were examined to assess the range and distribution of responses. These analyses provided foundational insights into the sample characteristics and informed subsequent inferential analyses.

Measurement Model Assessment

The assessment of the measurement model focused on evaluating the reliability and validity of the constructs. Internal consistency reliability was assessed using Composite Reliability (CR) and Cronbach's alpha coefficients, with values above 0.7 considered acceptable reliability. Meanwhile, convergent validity was evaluated by examining the Average Variance Extracted (AVE) for each construct, with values exceeding 0.5 suggesting that the construct explains more than half of the variance of its indicators.

Discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of the AVE of each construct with the correlations between that construct and others in the model. To verify that each construct was conceptually distinct, the Fornell-Larcker criterion required that the square root of AVE for each construct be greater than its highest correlation with any other construct in the model. Additionally, the cross-loadings were examined to confirm that each item loaded more strongly on its assigned construct than on other constructs. The steps verified that the measurement model met the necessary conditions for reliability and validity (Li et al., 2020).

Structural Model Assessment

Following the validation of the measurement model, the structural model was evaluated to test the proposed hypotheses and examine the relationships between constructs. Path coefficients (β-values) were estimated using PLS, and their significance was determined through bootstrapping with 5,000 resamples (Streukens & Leroi-Werelds, 2016). The hypotheses were tested based on the t-values and p-values of such path coefficients, with a significance threshold of $p < 0.05$.

In addition to hypothesis testing, the structural model's explanatory power was evaluated employing the coefficient of determination (R^2), which indicates the proportion of variance in the dependent variables that is explained by the independent variables. Higher R^2 values suggest a stronger explanatory power of the model. Predictive relevance (Q^2) was also examined using blindfolding procedure, with positive Q^2 values reflecting that it possesses predictive accuracy for the endogenous constructs (Mehta, 2021).

Model Fit Assessment

Although PLS-SEM is mainly a predictive modeling approach rather than a covariance-based method focused on model fit, several goodness-of-fit indicators were evaluated to ensure the adequacy of the model. The Standardized Root Mean Square Residual (SRMR) was applied to assess the model's overall fit, with values below 0.08 showing a good fit (Beribisky & Cribbie, 2024). The Normed Fit Index (NFI) was also reported, with values above 0.90 representing an acceptable model fit (Davey et al., 2005).

Mediation and Moderation Analyses

Mediation and moderation analyses were performed to obtain deeper insights into the mechanisms underlying the behavioural intention. Mediation effects were tested using the bootstrapped indirect effects approach to determine whether constructs served as intermediaries in the relationships between independent and dependent variables. These analyses provided a more meticulous understanding of the factors influencing the pharmacist's acceptance of ML-driven predictors and helped to identify potential boundary conditions for the generalizability of the findings (Matthews & Matthews, 2017).

Ethical Approval

Ethical approval for the study was obtained from the Institutional Review Board of the Ethics Committee for Research and Training, PKU Muhammadiyah Gamping Hospital, Sleman Regency, Special Region of Yogyakarta, Indonesia with approval number 169/KEP-PKU/X/2023, confirming adherence to ethical standards in research involving human subjects.

RESULTS

Study Participants

The demographic distribution of the participants provides a comprehensive understanding of the pharmacy's characteristics and potential influences on the adoption of ML-driven ABR predictors. Among the 235 hospital pharmacists surveyed, as shown in Table 2, 56.6% (n = 133) were female, while 43.4% (n = 102) were male, describing a balanced gender representation. Regarding the age distribution, it was revealed that the majority of participants were in their early to mid-career stages, with 40.9% (n = 96) between 31–40 years, followed by 31.5% (n = 74) between 21–30 years, 20.0% (n = 47) between 41–50 years, and 7.7% (n = 18) aged 51 years or older. Such predominance of younger professionals suggests that the study takes insights from individuals more likely to be open to technological advancements in the pharmacy practice (Torous et al., 2021).

Table 2

Demographic Information of the Study Participants (n=235)

Demographic Variable	N (%)
Gender	
Male	102 (43.4)
Female	133 (56.6)
Age (Years)	
21 – 30	74 (31.5)
31 – 40	96 (40.9)
41 – 50	47 (20.0)
51 – 60	8 (7.7)
Education Level	
Diploma in Pharmacy (D. Pharm)	45 (19.1)

(continued)

Demographic Variable	N (%)
Bachelor's Degree in Pharmacy (B. Pharm)	151 (64.3)
Master's Degree in Pharmacy (M. Pharm)	39 (16.6)
Years of Work Experience	
< 1 year	18 (7.7)
1 – 5 years	82 (34.9)
6 – 10 years	75 (31.9)
> 10 years	60 (25.5)
Hospital Type	
Public Hospital	142 (60.4)
Private Hospital	93 (39.6)
Hospital Bed Capacity	
< 100 beds	56 (23.8)
100 – 200 beds	91 (38.7)
201 – 300 beds	65 (27.7)
> 300 beds	23 (9.8)
Clinical Decision Support System (CDSS) Usage	
Never Used CDSS	194 (82.6)
Occasionally Uses CDSS	36 (15.3)
Regularly Uses CDSS	5 (2.1)
Exposure to ML / AI in CDSS	
No Exposure	218 (92.8)
Minimal familiarity (e.g., ChatGPT only)	13 (5.5)
Previously Used AI-driven CDSS	4 (1.7)
Familiarity with ML / AI	
Not Familiar	183 (77.9)
Heard About It but Never Used	39 (16.6)
Somewhat Familiar (Basic Knowledge)	10 (4.3)
Familiar (Used for Non-pharmacy Purposes)	3 (1.3)

Educational qualifications varied, with the majority holding a Bachelor's degree in pharmacy (64.3%, n = 151), while 16.6% (n = 39) held a Master's degree in pharmacy and 19.1% (n = 45) a Diploma in Pharmacy. It may influence the respondent's familiarity with advanced technologies such as ML-driven CDSS since postgraduate education often includes exposure to clinical informatics and emerging AI applications in healthcare (Al-Roomi et al., 2024). Professional experience was another key variable assessed, as familiarity with digital health tools often correlates with years of practice and institutional exposure to technology-driven initiatives. A substantial portion of respondents had 1–5 years of experience (34.9%, n = 82), followed by 6–10 years (31.9%, n = 75), and more than 10 years (25.5%, n = 60), while 7.7% (n = 18) had less than one year of experience. The employment distribution between public and private hospitals was also examined, revealing that 60.4% (n = 142) of pharmacists worked in public hospitals, while 39.6% (n = 93) were employed in private institutions. These findings represent a higher representation of pharmacists, potentially reflecting differences in institutional support, funding, and exposure to digital health initiatives.

Hospital capacity was another relevant variable, with 38.7% (n = 91) of respondents working in hospitals with 100–200 beds, 27.7% (n = 65) in hospitals with 201–300 beds, 23.8% (n = 56) in facilities with fewer than 100 beds, while 9.8% (n = 23) in larger hospitals with over 300 beds. It reflects potential disparities in access to the healthcare technologies and IT infrastructure, which could impact pharmacist's willingness and ability to integrate ML-driven CDSS into their practice (Blease et al., 2021; Silva et al., 2024).

Despite the increasing adoption of AI technologies in healthcare, a significant 82.6% (n = 194) of pharmacists reported never having used a CDSS, while 15.3% (n = 36) occasionally used CDSS, and only 2.1% (n = 5) regularly used CDSS in their daily practice. It demonstrates a substantial gap in digital technology adoption, with most pharmacists lacking experience with AI-based decision-making tools. When specifically assessing exposure to ML and AI-driven CDSS, 92.8% (n = 218) of respondents had never encountered these technologies, while 5.5% (n = 13) had minimal familiarity (e.g., use of ChatGPT), and only 1.7% (n = 4) had previously used an AI-driven CDSS. Similarly, when evaluating familiarity with ML/AI concepts, 77.9% (n = 183) were not familiar at all, while 16.6% (n = 39) had heard of ML but never used it, and only 5.6% (n = 13) reported some level of familiarity with the AI technologies. These findings align with previous studies indicating limited exposure to AI-driven healthcare tools among pharmacists, which may be a barrier to adoption unless targeted training interventions are implemented (Jarab et al., 2023).

Measurement Model Assessment (Outer Model)

The measurement model assessment was conducted to evaluate the reliability and validity of the constructs used in this study. The PLS-SEM was used via SmartPLS v3.2.9 to confirm that the latent constructs effectively measured the intended theoretical dimensions. The validation process was structured in three stages: convergent validity, discriminant validity, and reliability analysis. Convergent validity was assessed to confirm that the indicators adequately measured their constructs (Marliani et al., 2023), while discriminant validity was evaluated to ensure that each construct was empirically distinct from the others (Afthanorhan et al., 2021). Lastly, reliability analysis was performed to determine the internal consistency of the measurement items, thereby providing robustness in construct measurement (Malapane & Ndlovu, 2024). These procedures align with best practices in PLS-SEM applications in healthcare technology adoption research, which require rigorous testing of the measurement model before proceeding with structural model analysis (Sarstedt et al., 2023).

Convergent Validity

Convergent validity assesses how well multiple items measuring the same construct correlate. It is evaluated by factor loadings (>0.7) and Average Variance Extracted (AVE >0.5) (Fiati et al., 2025). Table 3 shows that all factor loadings exceeded 0.7, confirming strong item reliability, while AVE values (0.726–0.812) indicate that the constructs effectively captured variance.

Table 3

Factor Loadings and Average Variance Extracted (AVE) Values

Construct	Item Code	Loading Factor	AVE
Facilitating Conditions (FC)	FC1	0.825	0.765
	FC2	0.885	
	FC3	0.894	
	FC4	0.893	
Perceived Risk (PR)	PR1	0.908	0.812
	PR2	0.884	
	PR3	0.907	
	PR4	0.905	
Trust in Technology (TT)	TT1	0.871	0.741
	TT2	0.874	
	TT3	0.842	
	TT4	0.856	
Social Influence (SI)	SI1	0.866	0.744
	SI2	0.821	
	SI3	0.884	
	SI4	0.879	
Perceived Ease of Use (PEOU)	PEOU1	0.807	0.726
	PEOU2	0.868	
	PEOU3	0.851	
	PEOU4	0.88	
Perceived Usefulness (PU)	PU1	0.798	0.745
	PU2	0.881	
	PU3	0.891	
	PU4	0.879	
Behavioural Intention (BI)	BI1	0.888	0.78
	BI2	0.892	
	BI3	0.903	
	BI4	0.849	

Discriminant Validity

Discriminant validity confirms that each construct is empirically distinct from the other constructs within the model (Matthes & Ball, 2019). The Fornell-Larcker criterion was applied, where the square root of AVE for each construct must exceed its correlation with other constructs. As shown in Table 4 below, diagonal values (square roots of AVE) are higher than the inter-correlations, confirming strong discriminant validity.

Table 4

Fornell-larcker Criterion for Discriminant Validity

Constructs	BI	FC	PEOU	PR	PU	SI	TT
Behavioural Intention (BI)	0.883						
Facilitating Conditions (FC)	0.664	0.875					
Perceived Ease of Use (PEOU)	0.727	0.623	0.852				
Perceived Risk (PR)	0.196	0.382	0.221	0.901			
Perceived Usefulness (PU)	0.766	0.606	0.74	0.317	0.863		
Social Influence (SI)	0.722	0.62	0.727	0.207	0.684	0.863	
Trust in Technology (TT)	0.693	0.725	0.612	0.327	0.646	0.637	0.861

The cross-loadings in Table 5 confirm discriminant validity, as each indicator demonstrates higher loadings on its respective construct than all others. This strong differentiation between constructs reinforces their empirical distinctiveness, ensuring that each variable measures a unique aspect of the research model, thus supporting the robustness and validity of the measurement framework.

Table 5

Cross-loadings of Measurement Items

Item	BI	FC	PEOU	PR	PU	SI	TI
BI1	0.888	0.555	0.655	0.223	0.726	0.644	0.588
BI2	0.892	0.572	0.664	0.112	0.648	0.672	0.578
BI3	0.903	0.609	0.659	0.180	0.716	0.631	0.628
BI4	0.849	0.610	0.588	0.178	0.613	0.603	0.656
FC1	0.595	0.825	0.534	0.372	0.569	0.527	0.564
FC2	0.557	0.885	0.491	0.291	0.482	0.541	0.613
FC3	0.544	0.894	0.55	0.349	0.514	0.521	0.672
FC4	0.623	0.893	0.599	0.324	0.556	0.579	0.68
PEOU1	0.567	0.526	0.807	0.139	0.575	0.581	0.506
PEOU2	0.644	0.541	0.868	0.167	0.632	0.649	0.534
PEOU3	0.612	0.509	0.851	0.216	0.61	0.598	0.485
PEOU4	0.65	0.549	0.88	0.226	0.699	0.648	0.559
PR1	0.202	0.324	0.217	0.908	0.298	0.214	0.285
PR2	0.191	0.320	0.185	0.884	0.293	0.197	0.272
PR3	0.141	0.335	0.196	0.907	0.285	0.16	0.284
PR4	0.172	0.391	0.198	0.905	0.269	0.174	0.332
PU1	0.634	0.559	0.661	0.289	0.798	0.646	0.644
PU2	0.692	0.533	0.636	0.255	0.881	0.596	0.556
PU3	0.672	0.499	0.618	0.266	0.891	0.552	0.512
PU4	0.641	0.497	0.633	0.284	0.879	0.562	0.51
SI1	0.621	0.533	0.642	0.19	0.561	0.866	0.555
SI2	0.606	0.551	0.579	0.233	0.579	0.821	0.48
SI3	0.599	0.513	0.629	0.159	0.596	0.884	0.569
SI4	0.662	0.545	0.657	0.138	0.623	0.879	0.59

(continued)

Item	BI	FC	PEOU	PR	PU	SI	TI
TT1	0.567	0.605	0.503	0.301	0.537	0.537	0.871
TT2	0.575	0.625	0.496	0.278	0.523	0.526	0.874
TT3	0.586	0.604	0.501	0.277	0.496	0.526	0.842
TT4	0.648	0.656	0.597	0.27	0.654	0.598	0.856

Reliability Analysis

Reliability analysis was conducted using Cronbach's Alpha (CA) and Composite Reliability (CR) to measure internal consistency (Kalkbrenner, 2023). A Cronbach's Alpha above 0.7 and Composite Reliability exceeding 0.7 confirm construct reliability. As seen in Table 6 below, all constructs met the criteria, showing strong internal consistency and measurement reliability.

Table 6

Reliability Analysis of the Study

Constructs	Cronbach's Alpha	CR
Behavioural Intention	0.906	0.934
Facilitating Conditions	0.898	0.929
Perceived Ease of Use	0.874	0.914
Perceived Risk	0.923	0.945
Perceived Usefulness	0.885	0.921
Social Influence	0.885	0.921
Trust in Technology	0.884	0.92

Variance Inflation Factor (VIF) Analysis

Multicollinearity was evaluated using the Variance Inflation Factor (VIF), where values below 5.0 indicate an absence of significant multicollinearity. As shown in Table 7, all constructs exhibited VIF values well below the threshold, confirming that collinearity issues were not present and that the model maintains statistical independence among predictor variables.

Table 7

VIF Values

BI	FC	PEOU	PR	PU	SI	TT
2.81	1.969	1.827	3.361	1.697	2.353	3.019
2.817	2.946	2.4	2.913	2.691	1.928	3.055
3.097	2.971	2.171	3.587	2.925	2.64	2.175
2.215	2.707	2.543	3.31	2.657	2.513	2.174

Heterotrait-monotrait Ratio (HTMT) Analysis

The HTMT ratio, a stricter criterion for discriminant validity, as shown in Table 8, was utilised as an additional measure. As values were below 0.9, it satisfied discriminant validity requirements.

Table 8

Results of Heterotrait-monotrait Ratio (HTMT) Analysis

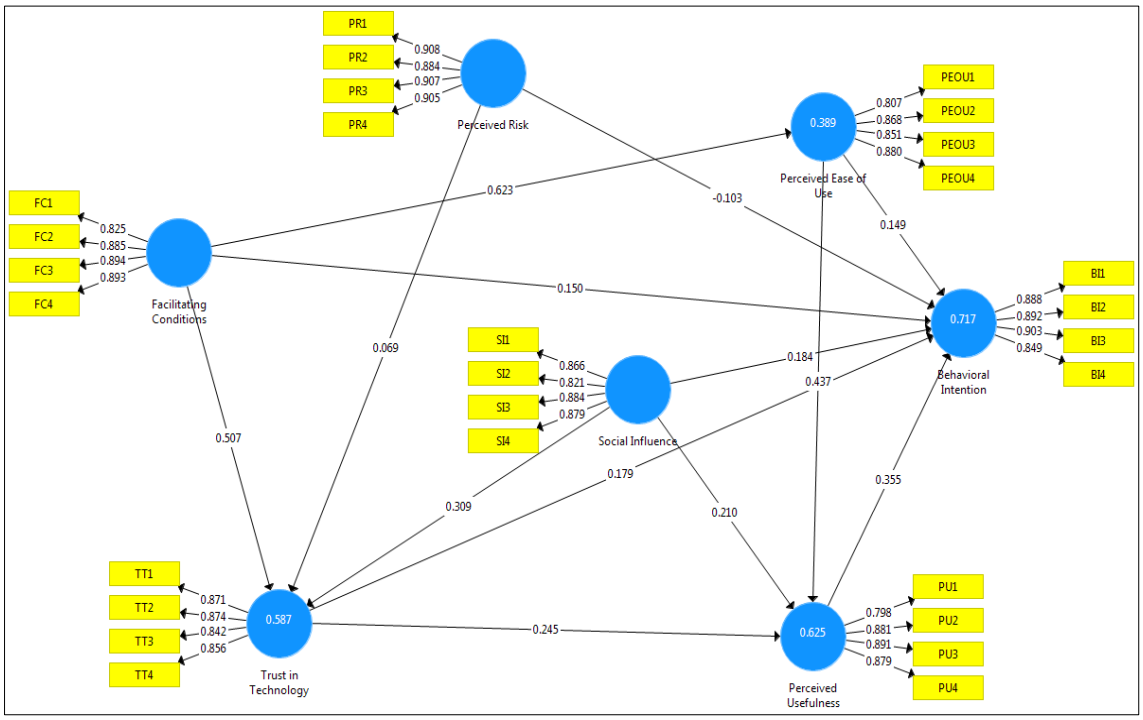
Variable	BI	FC	PEOU	PR	PU	SI	TT
Behavioural Intention							
Facilitating Conditions	0.736						
Perceived Ease of Use	0.815	0.702					
Perceived Risk	0.214	0.418	0.244				
Perceived Usefulness	0.854	0.679	0.839	0.351			
Social Influence	0.806	0.696	0.826	0.231	0.771		
Trust in Technology	0.772	0.81	0.692	0.361	0.724	0.717	

Structural Model Assessment (Inner Model)

The structural model assessment, shown in Figure 2, was conducted to assess the relationships among the latent variables and to test the hypothesised paths within the research framework. This analysis was performed using PLS-SEM via SmartPLS v3.2.9, following the verification of the measurement model. It involved evaluating the coefficient of determination (R^2), predictive relevance (Q^2), and hypothesis testing through path coefficients, t-values, and p-values.

Figure 2

Structural Model of the Study



Coefficient of Determination (R^2) Analysis

R^2 was applied to evaluate the explanatory power of the independent variables on the dependent constructs. R^2 values describe the proportion of variance in the dependent variable explained by the predictor variables, with higher values demonstrating stronger predictive capability. As presented in Table 8, the R^2 value for BI was 0.717, meaning that 71.7% of the variance in BI was explained by the independent variables, with the remaining 28.3% attributed to external factors not captured in the model. The R^2 values for PU (0.625), TT (0.587), and PEOU (0.389) indicate a moderate-to-strong explanatory power, reflecting that all the constructs effectively predict user intention toward ML adoption. Such findings are consistent with prior research on TAM extensions in healthcare technology adoption, where the R^2 values between 0.5 and 0.8 indicate a strong predictive model (Chismar & Wiley-Patton, 2005).

Table 9

Coefficient of Determination (R^2) Values

Construct	R^2 Value	Adjusted R^2 Value
Behavioural Intention (BI)	0.717	0.709
Perceived Ease of Use (PEOU)	0.389	0.386
Perceived Usefulness (PU)	0.625	0.621
Trust in Technology (TT)	0.587	0.581

Predictive Relevance (Q^2) Analysis

Stone-Geisser's Q^2 values were calculated using the blindfolding technique in SmartPLS, a widely used method in structural equation modelling to evaluate the model's predictive accuracy. A Q^2 value greater than zero indicates the model has predictive relevance, confirming its ability to generate meaningful future predictions rather than merely fitting past data. As presented in Figure 3, the results reveal that all Q^2 values are positive, reinforcing the model's strong predictive validity across multiple constructs. Specifically, BI (Q^2 = 0.547) exhibited the highest predictive relevance, which signifies that the independent variables of this study explain a substantial portion of its variance.

PU (Q^2 = 0.455) and TT (Q^2 = 0.428) also demonstrated strong predictive capabilities, indicating that these constructs are crucial in influencing pharmacists' AI adoption behaviours. These findings further establish the robustness of the research model, demonstrating its ability to provide reliable forecasts of pharmacist adoption trends for AI-driven decision-support tools. Table 10 comprehensively summarises the Q^2 values across all constructs, reinforcing the models' utility in predicting real-world adoption patterns.

Figure 3

Structural Model of the Predictive Relevance

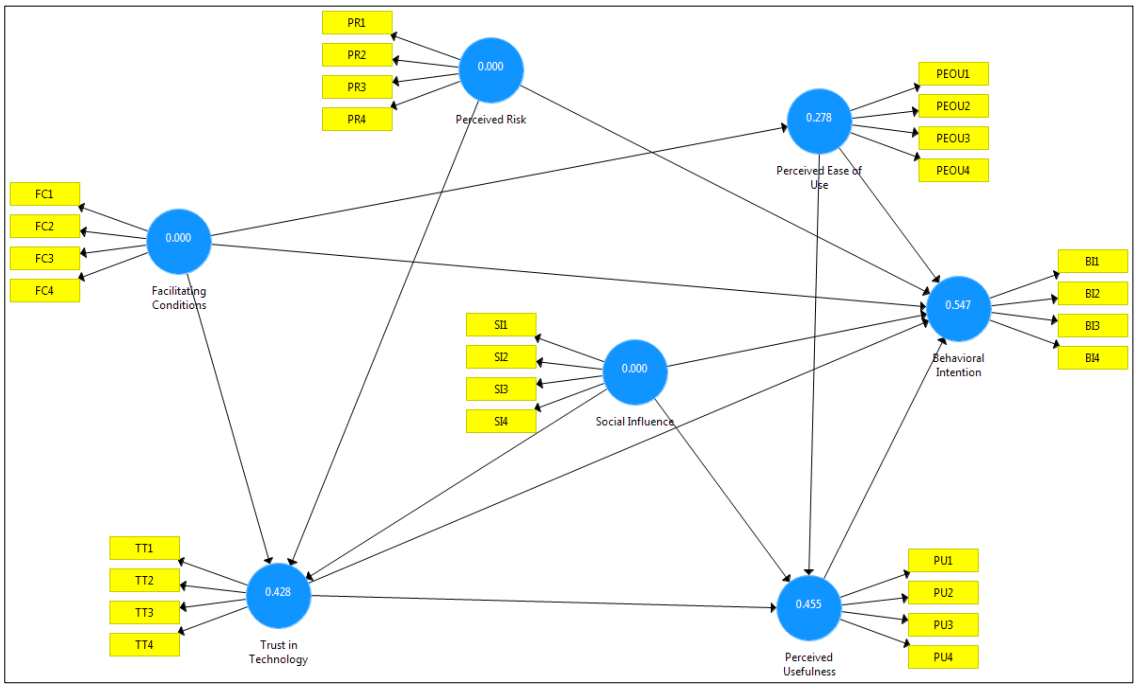


Table 10

Predictive Relevance (Q^2) Values

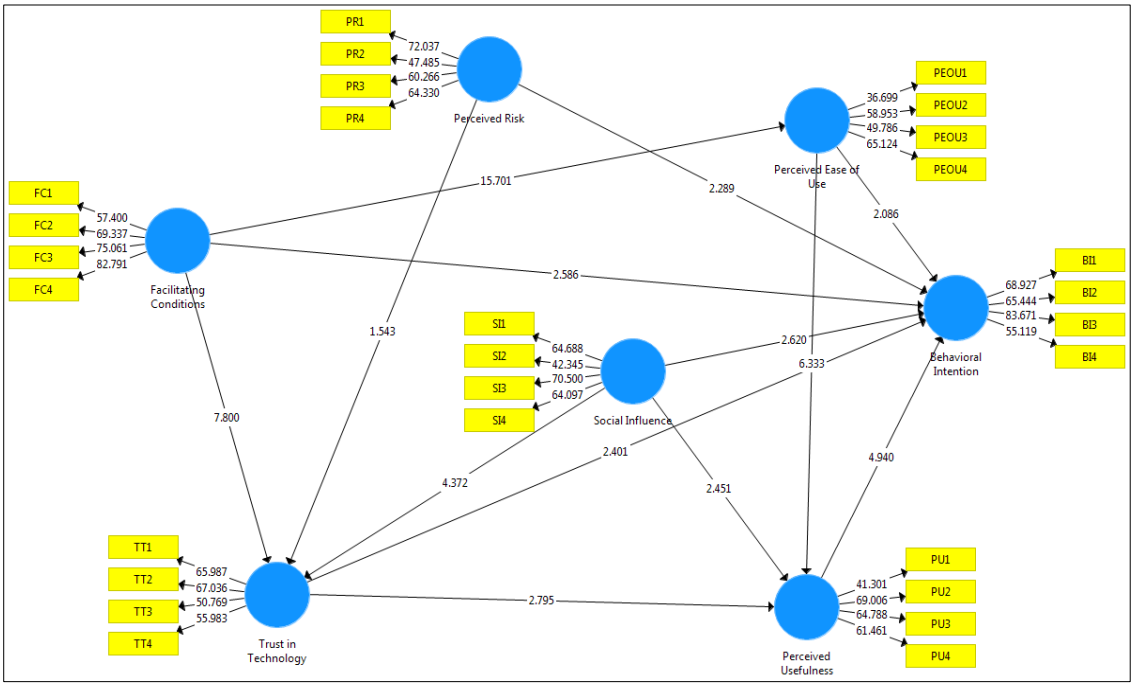
Construct	Q^2 Value	Predictive Relevance
Behavioural Intention (BI)	0.547	High Predictive Relevance
Perceived Ease of Use (PEOU)	0.278	Moderate Predictive Relevance
Perceived Usefulness (PU)	0.455	High Predictive Relevance
Trust in Technology (TT)	0.428	High Predictive Relevance

Hypothesis Testing and Path Coefficients

The hypothesised relationships between constructs were tested using path coefficients (β), t-statistics, and p-values. A t-value greater than 1.96 and p-value less than 0.05 were used to verify statistical significance at a 95% confidence level (Del Pino, 2021; Grech & Eldawlatly, 2023). The hypothesis testing results are summarised in Figure 4 and Table 11, where 12 out of 13 hypotheses were supported, confirming the theoretical validity of the extended TAM framework in ML adoption among hospital pharmacists.

Figure 4

Hypothesis Test of the Study



The results indicate that PU had the strongest influence on BI (β = 0.355, p < 0.001), suggesting that pharmacists are more likely to adopt ML-driven ABR predictors if they improve clinical decision-making and patient outcomes. PEOU significantly impacted both PU (β = 0.437) and BI (β = 0.149), reinforcing the importance of system usability, interface simplicity, and training availability in AI acceptance. Moreover, SI was positively associated with TT (β = 0.309) and BI (β = 0.184), highlighting the critical role of peer recommendations, institutional support, and professional endorsements in shaping pharmacists' attitudes toward AI adoption. Conversely, PR negatively influenced BI (β = -0.103, p = 0.023), indicating that concerns regarding ML accuracy, liability, and ethical implications remain significant barriers to adoption. These findings suggest that minimising risk perceptions through transparent AI models and regulatory safeguards could enhance pharmacists' confidence in ML-driven decision-support tools, fostering broader acceptance in clinical practice.

Table 11

Hypothesis Testing Results

Hypothesis	Path	β Value	t-Statistic	p-Value	Result
H1	PU → BI	0.355	4.94	0.000	Supported
H2	PEOU → PU	0.437	6.333	0.000	Supported
H3	PEOU → BI	0.149	2.086	0.037	Supported
H4	SI → BI	0.184	2.62	0.009	Supported
H5	TT → PU	0.245	2.795	0.005	Supported
H6	TT → BI	0.179	2.401	0.017	Supported
H7	FC → BI	0.15	2.586	0.010	Supported
H8	FC → PEOU	0.623	15.701	0.000	Supported
H9	PR → BI	-0.103	2.289	0.023	Supported

(continued)

Hypothesis	Path	β Value	t-Statistic	p-Value	Result
H10	PR → TT	0.069	1.543	0.124	Not Supported
H11	SI → TT	0.309	4.372	0.000	Supported
H12	SI → PU	0.21	2.451	0.015	Supported
H13	FC → TT	0.507	7.8	0.000	Supported

DISCUSSIONS

Key Findings of the Study

This study provides significant insights into the factors influencing hospital pharmacist's BI to adopt ML-driven ABR predictors. The results demonstrate that PU, PEOU, TT, SI, and FC positively influence BI, with 12 out of 13 proposed hypotheses being supported. Among these factors, PU exhibited the strongest influence on BI ($\beta = 0.355$, $p < 0.001$), indicating that pharmacists are more likely to adopt ML-based decision-support tools if they perceive them as beneficial for enhancing clinical efficiency and decision-making accuracy. Such finding aligns with previous studies on AI adoption in healthcare, where PU is consistently identified as the primary determinant of technology acceptance among clinicians and pharmacists (Bennani & Oumlil, 2010; Sezgin & Özkan-Yıldırım, 2016; Shadangi et al., 2018).

The findings also reveal that PEOU significantly influences both PU ($\beta = 0.437$, $p < 0.001$) and BI ($\beta = 0.149$, $p = 0.037$), highlighting that the usability and simplicity of ML-driven tools play a crucial role in their adoption by pharmacists. If pharmacists find the tools intuitive and easy to navigate, they are more likely to recognise their usefulness and incorporate them into their clinical workflows. Prior research has emphasised similar concerns regarding AI usability in healthcare fields, showing that AI adoption remains limited when users perceive the technology as complex or disruptive to established routines (Al Wael et al., 2024). The role of SI was also found to be significant, positively influencing BI ($\beta = 0.184$, $p = 0.009$) and TT ($\beta = 0.309$, $p < 0.001$), suggesting that some factors, such as peer recommendations, managerial support, and professional endorsement, are critical enablers of AI adoption. It is consistent with studies that show healthcare professionals are more likely to adopt AI-driven decision-support tools when their colleagues and institutional leaders advocate for their use (Ayorinde et al., 2023; Haller & Reynolds, 2024a).

Another notable finding is the negative influence of PR on BI ($\beta = -0.103$, $p = 0.023$), which underlines pharmacists' concerns about the accuracy, reliability, and potential legal and ethical implications of relying on ML-generated recommendations. It echoes a previous study that identified fear of algorithmic errors, liability concerns, and a lack of transparency as major barriers to AI technology adoption in clinical practice (Razai et al., 2024). However, PR was not significantly associated with TT ($\beta = 0.069$, $p = 0.124$), indicating that while pharmacists perceive some risks associated with AI adoption, these concerns do not necessarily affect their trust in the technology itself. It suggests that pharmacists may be willing to trust AI-driven decision support tools provided that appropriate safeguards, validation processes, and human oversight mechanisms are in place (Bücker et al., 2024).

Practical Implications

These study findings provide several critical practical implications for hospital administrators, policymakers, and AI technology developers to facilitate the effective adoption of ML-driven ABR predictors in hospital pharmacy practice. Given the strong influence of PU ($\beta = 0.355$, $p < 0.001$) on BI, hospital administrators must prioritise pharmacy personnel-oriented AI training programmes that focus on demonstrating real-world clinical benefits and efficiency improvement. Hospital pharmacists need hands-on training, simulations, and case-based learning modules to understand how ML algorithms generate predictions and how these tools can complement clinical decision-making. Without such training initiatives, even the most advanced AI-driven decision-support tools risk low adoption due to a lack of familiarity and confidence (Dingel et al., 2024; Huang et al., 2023).

Given that FC significantly influences PEOU ($\beta = 0.623$, $p < 0.001$) and BI ($\beta = 0.150$, $p = 0.010$), hospital leadership must invest in strengthening IT infrastructure and technical support systems to facilitate seamless AI integration into pharmacists' clinical workflows. It includes upgrading electronic health record (EHR) systems to support AI-driven decision tools, ensuring smooth interoperability, and providing 24/7 technical support for troubleshooting (Haller & Reynolds, 2024b; Sriharan et al., 2024). Meanwhile, from a policy standpoint, the findings on PR negatively influencing BI ($\beta = -0.103$, $p = 0.023$) underline the need for comprehensive AI governance frameworks that clearly define accountability, liability, and ethical considerations in AI-assisted decision-making. Policymakers should guarantee that pharmacists have clear guidelines on how to interpret AI-generated recommendations and establish a legal framework for handling AI-driven prescription errors and liability disputes (Chen & Wang, 2024). Finally, since SI significantly impacts BI ($\beta = 0.184$, $p = 0.009$), professional organisations and hospital management must actively promote AI adoption through peer discussions, expert-led workshops, and leadership endorsements. Pharmacists are more likely to adopt AI-driven decision tools if senior colleagues, professional networks, and hospital leadership advocate for their integration into routine practice (De Domenico et al., 2023).

Limitations of the Study

Despite its contributions, this study has limitations. First, its geographic scope was limited to hospital pharmacists in Indonesia, meaning that the findings may not be fully generalisable to pharmacists in countries with different healthcare infrastructures, AI readiness levels, and regulatory environments. Future research should conduct cross-country comparative studies to examine how AI technology adoption trends vary across diverse healthcare systems, regulatory frameworks, and cultural contexts (Krishnamoorthy et al., 2022; Townsend et al., 2023). Second, this study employed a cross-sectional design, capturing pharmacists' perceptions at a single time. However, adopting AI technology is a dynamic process that evolves with increasing exposure, policy changes, and technological improvements. Future research should use longitudinal studies to examine how pharmacists' attitudes toward ML-driven CDSS evolve as AI technologies become more integrated into healthcare workflows (Zhang et al., 2024). Additionally, qualitative methods such as in-depth interviews and focus groups should be employed to explore the pharmacist's concerns, expectations, and real-world experiences with AI technology adoption in greater depth. Such insights could help refine AI implementation strategies and develop more user-centric decision-support tools that align with pharmacists' clinical needs.

CONCLUSION

This study highlights the key factors influencing hospital pharmacists' adoption of ML-driven antibiotic resistance predictors, emphasising the roles of Perceived Usefulness, Trust in Technology, Facilitating Conditions, and Social Influence. To enhance adoption, hospital administrators should invest in AI training programmes, IT infrastructure, and peer-learning initiatives, while policymakers must address pharmacists' risk concerns through regulatory frameworks and AI transparency measures. Future research should explore longitudinal adoption trends, qualitative insights, and cross-country comparisons to refine AI implementation strategies in pharmacy practice and antimicrobial stewardship programmes.

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