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ARTIFICIAL INTELLIGENCE–GUIDED PRECISION ANTIBIOTIC STEWARDSHIP FOR COMBATING ANTIMICROBIAL RESISTANCE IN PAKISTANI TERTIARY CARE HOSPITALS

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Abstract

Antimicrobial resistance (AMR) is a major challenge for tertiary care hospitals, where inappropriate antibiotic use can accelerate resistant infections. This study examined an artificial intelligence (AI)-guided precision antibiotic stewardship framework for AMR risk prediction in Pakistani tertiary care hospitals. A quantitative predictive design integrated clinical, microbiological, hospitalization, and previous antibiotic-use indicators. Multiple machine-learning algorithms were evaluated using standard performance metrics, while explainable AI was applied to identify important predictors. The findings showed that Gradient Boosting achieved the highest performance (accuracy = 89.3%; AUC = .95). Previous antibiotic exposure, microbiological resistance indicators, previous hospitalization, and clinical severity were the major predictors. Healthcare professionals also reported relatively high perceived usefulness and intention to use AI-assisted stewardship. The findings suggest that explainable AI can complement conventional stewardship by supporting individualized AMR-risk assessment and more informed antibiotic selection.

INTRODUCTION

Antimicrobial resistance (AMR) has become a major global health threat, reducing the effectiveness of antibiotics and increasing morbidity, mortality, and healthcare costs. The global burden of bacterial AMR remains substantial, with resistant infections contributing to millions of deaths annually, while the burden is expected to increase without effective interventions (GBD 2021 Antimicrobial Resistance Collaborators, 2024). The World Health Organization (WHO, 2024) has identified multiple high- and critical-priority resistant pathogens, emphasizing the need for improved antimicrobial surveillance, infection prevention, and antibiotic stewardship.

Antibiotic stewardship aims to ensure appropriate antibiotic selection, dose, route, duration, and de-escalation while minimizing unnecessary exposure and resistance. However, conventional stewardship approaches frequently depend on manual prescription review, laboratory reports, clinical judgment, and retrospective surveillance. These approaches can be resource-intensive and may not adequately exploit the large volumes of clinical, microbiological, and prescribing data generated by tertiary hospitals. Recent studies indicate that artificial intelligence (AI) and machine learning (ML) can analyze these heterogeneous data to predict antimicrobial resistance, identify inappropriate prescribing, support antibiotic selection, and improve stewardship surveillance (Perrella et al., 2024; Pérez de la Lastra et al., 2024).

ML-based AMR prediction has demonstrated promising discriminatory performance, particularly when demographic characteristics, previous antimicrobial exposure, microbiological findings, and clinical variables

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are integrated. However, existing evidence is concentrated in high-resource settings, and external validation and prospective clinical implementation remain limited (Lv & Wang, 2024). Explainability is also important because clinicians need to understand the factors underlying algorithmic recommendations before incorporating them into antibiotic decisions.

The challenge is particularly relevant in Pakistan. Evidence from Pakistani tertiary hospitals has documented inappropriate antibiotic prescribing, inadequate culture-guided therapy, limited institutional guidelines, and substantial opportunities for stewardship interventions. Recent hospital studies have identified excessive antibiotic use and gaps in stewardship implementation, while national evidence supports strengthening surveillance, diagnostic capacity, and institutional antimicrobial stewardship programs. Pakistan's National Action Plan for Antimicrobial Resistance 2.0 (2024–2028) further emphasizes surveillance, infection prevention, antimicrobial stewardship, and coordinated action against AMR.

Despite these developments, limited evidence exists on locally developed and clinically integrated AI systems for precision antibiotic stewardship in Pakistani tertiary care hospitals. Most available research evaluates antibiotic utilization or AMR patterns separately, whereas comparatively limited work integrates patient characteristics, microbiological results, previous antibiotic exposure, resistance patterns, and prescribing information into an explainable predictive framework. Therefore, this study proposes an AI-guided precision stewardship approach that can support individualized antibiotic selection, early AMR risk prediction, and timely stewardship intervention while retaining clinician oversight.

Problem Statement

Antimicrobial resistance is an escalating challenge for Pakistani healthcare institutions, particularly tertiary care hospitals where critically ill patients frequently receive broad-spectrum and empiric antibiotics. Evidence from Pakistani hospitals indicates inappropriate prescribing, insufficient culture-guided treatment, inconsistent antimicrobial guidelines, and weaknesses in formal stewardship structures. These factors can increase unnecessary antibiotic exposure and contribute to the selection and transmission of resistant organisms.

Conventional antimicrobial stewardship relies substantially on retrospective prescription review, clinical expertise, microbiological testing, and periodic surveillance. Although these approaches remain essential, they may be insufficient for rapidly identifying patients at high risk of resistant infections and providing timely, individualized antibiotic recommendations. AI and ML offer the capacity to integrate large-scale clinical, laboratory, microbiological, and prescribing datasets and generate patient-specific predictions. Nevertheless, much of the existing AI evidence originates from high-resource healthcare systems, with limited prospective validation and relatively little evidence from Pakistani tertiary hospitals.

A further research gap concerns explainability and clinical integration. High-performing algorithms may remain difficult for clinicians to interpret, potentially limiting trust, adoption, and accountability. Consequently, there is a need for locally relevant, interpretable AI models that predict resistance risk and support appropriate antibiotic decisions while fitting existing antimicrobial stewardship workflows.

This study addresses this gap by developing an AI-guided precision antibiotic stewardship framework for Pakistani tertiary care hospitals. The proposed approach integrates patient-level clinical characteristics, microbiological findings, previous antibiotic exposure, and resistance-related information to support timely and evidence-informed antibiotic decisions. The study therefore connects Pakistan's urgent AMR and stewardship needs with emerging AI-based predictive capabilities.

Research Questions

1. What clinical, microbiological, and prescribing factors are significantly associated with antimicrobial resistance in Pakistani tertiary care hospitals?
2. To what extent can AI models accurately predict patient-level antimicrobial resistance risk?

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3. Which AI algorithm provides the most reliable prediction of antibiotic resistance and inappropriate antibiotic use?
4. Does AI-guided integration of clinical and microbiological information improve antibiotic-selection accuracy compared with conventional stewardship approaches?
5. How can explainable AI improve the transparency and clinical usefulness of antibiotic stewardship recommendations?

Research Objectives

1. To identify clinical, microbiological, and antibiotic-use factors associated with antimicrobial resistance in Pakistani tertiary care hospitals.
2. To develop an AI-based model for patient-level prediction of antimicrobial resistance risk.
3. To compare the predictive performance of alternative AI and machine-learning algorithms.
4. To evaluate whether AI-guided integration of clinical and microbiological information improves precision in antibiotic selection.
5. To apply explainable AI techniques to identify the principal factors underlying resistance predictions and stewardship recommendations.
6. To propose an AI-guided precision antibiotic stewardship framework suitable for Pakistani tertiary care hospitals.

Significance of the Study

Theoretical Significance

The study extends antimicrobial stewardship research by integrating AI-based predictive analytics with patient-level clinical and microbiological information. It contributes to the development of a precision stewardship perspective in which antibiotic decisions are informed by individualized resistance risk rather than generalized prescribing patterns.

Practical Significance

The proposed AI framework can assist clinicians, infectious-disease specialists, pharmacists, and stewardship teams in identifying patients at elevated risk of resistant infections and supporting appropriate antibiotic selection, de-escalation, and duration decisions. Explainable predictions may additionally improve transparency and clinician acceptance.

Policy Significance

The study supports Pakistan's national AMR priorities by providing an evidence-based framework for strengthening hospital surveillance, antimicrobial stewardship, diagnostic decision-making, and data-driven healthcare. AI-enabled stewardship could complement institutional antimicrobial guidelines and national AMR surveillance systems, provided that models undergo local validation, ethical review, and continuous performance monitoring.

Literature Review

Antimicrobial resistance (AMR) has increasingly become a major challenge for hospital-based healthcare because inappropriate antimicrobial exposure accelerates resistance, complicates treatment, and increases healthcare utilization. The WHO global research agenda identifies antimicrobial stewardship, improved diagnostics, surveillance, treatment optimization, and context-specific interventions as major priorities, particularly in resource-constrained settings.

Antimicrobial Stewardship and Hospital AMR

Antimicrobial stewardship (AMS) seeks to optimize antimicrobial selection, dose, route, and duration while achieving appropriate clinical outcomes and minimizing resistance and adverse effects. Evidence from Pakistani tertiary hospitals demonstrates substantial opportunities for improvement. A multicentre point-prevalence survey reported antibiotic use among approximately 75% of surveyed inpatients, with third-generation cephalosporins representing a major proportion of prescriptions and substantial gaps in institutional antimicrobial guidelines. More recent hospital evidence has similarly identified inappropriate prescribing and inadequate reliance on culture-sensitivity testing as important stewardship challenges.

Recent Pakistani evidence also demonstrates that structured stewardship interventions can produce measurable benefits. A tertiary-care study examining colistin resistance evaluated an AMS intervention incorporating preauthorization of a last-resort antibiotic, while

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recent work from Khyber Teaching Hospital examined pharmacist-led stewardship in hospital-acquired and ventilator-associated pneumonia. These findings indicate that stewardship interventions can be operationally valuable, but they also highlight the need for timely, data-driven mechanisms capable of supporting decisions before resistance information becomes available.

Artificial Intelligence in Antimicrobial Stewardship

AI and machine learning (ML) provide an opportunity to move AMS from predominantly retrospective audit toward predictive and patient-specific decision support. AI models can integrate demographic characteristics, clinical findings, previous antimicrobial exposure, microbiological results, laboratory parameters, and local resistance patterns to estimate the probability of resistant infection or inappropriate antimicrobial therapy.

A systematic review of AI applications in AMS identified applications including inappropriate-prescribing detection, antibiotic selection, and AMR prediction, with reported AUC values ranging from 0.64 to 0.992 across reviewed studies. However, the evidence was predominantly observational, indicating that promising predictive performance does not necessarily establish clinical effectiveness. A 2025 systematic review similarly reported applications of logistic regression, boosted-tree, and gradient-boosting approaches for intervention identification, antibiotic selection, resistance prediction, and dose optimization.

More broadly, recent reviews indicate that AI can exploit clinical, genomic, microbiological, and epidemiological information to predict AMR and potentially improve antimicrobial decision-making. Nevertheless, model heterogeneity, limited external validation, data quality, workflow integration, and implementation barriers remain important limitations. Thus, the literature supports AI as a potentially useful decision-support technology but does not justify replacing clinical judgment with automated recommendations.

Explainable AI and Clinical Decision Support

A critical limitation of AI-based healthcare systems is the interpretability of complex algorithms. In antimicrobial stewardship, clinicians need to understand why a model identifies a patient as being at high risk of resistance or recommends modification of antimicrobial therapy. Explainable and interpretable ML can provide feature-level information regarding the variables contributing to predictions and may therefore improve transparency, accountability, and clinician acceptance. Recent literature specifically identifies explainability as an important requirement for avoiding inappropriate reliance on black-box antimicrobial decision systems.

However, explainability does not establish causation. A variable identified as important by SHAP or another attribution method represents a contributor to a model's prediction rather than definitive evidence that the variable biologically causes antimicrobial resistance. Consequently, explainable AI should complement microbiological evidence, clinical assessment, and established stewardship guidelines.

Pakistani Context and Research Gap

Pakistan faces a particularly important need for locally validated AI-enabled stewardship. Its updated National Action Plan for Antimicrobial Resistance 2.0 (2024–2028) emphasizes governance, surveillance, infection prevention, antimicrobial stewardship, and coordinated action against AMR. Recent national analysis has nevertheless identified continuing gaps in surveillance, infection prevention and control, awareness, and implementation of AMR policies.

The literature therefore reveals three important gaps. First, Pakistani studies have predominantly examined antibiotic utilization, prescribing appropriateness, resistance patterns, or stewardship interventions separately rather than developing integrated predictive systems. Second, international AI research demonstrates considerable predictive potential but remains limited by external-validation and implementation problems. Third, comparatively limited research has combined patient-level clinical characteristics, microbiological information, previous antimicrobial exposure, local resistance patterns, and explainable AI within a single precision-stewardship framework specifically designed for Pakistani tertiary-care hospitals.

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The proposed study addresses this gap by developing an AI-guided precision antibiotic stewardship framework that integrates routinely available hospital data to predict resistance risk and support individualized antimicrobial decisions. The framework is intended to complement—not replace—microbiological testing, clinical expertise, and institutional stewardship protocols.

Underpinning Theory

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) provides an appropriate theoretical foundation for this study because successful AI implementation in antimicrobial stewardship depends not only on predictive accuracy but also on clinicians' willingness to use and trust the technology. TAM proposes that perceived usefulness and perceived ease of use influence users' attitudes and behavioral intention to adopt a technological system.

Applied to the present study, AI-guided antibiotic stewardship is more likely to be incorporated into clinical workflows when clinicians perceive that the system improves antibiotic-selection accuracy, reduces unnecessary prescribing, identifies AMR risk efficiently, and provides understandable recommendations. Explainable AI is particularly relevant because transparent model outputs can improve perceived usability and reduce uncertainty associated with black-box predictions.

The theoretical pathway can therefore be represented as:

AI predictive capability → perceived usefulness + explainability → clinician acceptance → AI-assisted stewardship adoption → improved antibiotic decision support.

TAM complements the technical component of the study by explaining the human and organizational dimension of AI adoption. Thus, while ML evaluates whether the system can predict AMR accurately, TAM provides a framework for understanding whether healthcare professionals are likely to accept and use such a system in practice.

Theoretical Contribution

The study extends TAM into the context of AI-enabled antimicrobial stewardship by incorporating explainability as an important mechanism supporting perceived usefulness and acceptance. This creates a link between predictive performance, interpretability, clinician adoption, and practical stewardship implementation. Such integration is particularly relevant for Pakistani tertiary hospitals, where technological infrastructure, clinical workflows, stewardship capacity, and human-resource constraints can influence successful AI implementation.

Hypotheses

H1: Clinical and microbiological risk factors have a positive and significant effect on antimicrobial resistance risk.

H2: Previous antibiotic exposure has a positive and significant effect on antimicrobial resistance risk.

H3: AI-guided precision stewardship significantly improves the accuracy of antimicrobial resistance prediction.

H4: Explainable AI significantly improves clinicians' perceived usefulness of AI-guided antibiotic stewardship.

H5: Clinicians' perceived usefulness of AI-guided stewardship positively influences their adoption of AI-assisted antibiotic prescribing.

H6: AI-guided precision antibiotic stewardship significantly improves appropriate antibiotic selection compared with conventional stewardship practices.

Methodology

Research Design

The study employed a quantitative, cross-sectional predictive research design to examine factors associated with antimicrobial resistance and evaluate the effectiveness and acceptance of AI-guided antibiotic stewardship. Clinical, microbiological, prescribing, and clinician-level data were analyzed to develop and assess AI-based prediction models.

Population

The population comprised adult patients admitted to selected Pakistani tertiary care hospitals who received systemic antibiotics during the study period, together with physicians, pharmacists, and antimicrobial-stewardship professionals involved in antibiotic prescribing or review. Patient data included

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demographic characteristics, clinical conditions, laboratory findings, microbiological results, previous antibiotic exposure, and antibiotic prescriptions.

Sampling Technique

A purposive sampling technique was employed to select tertiary care hospitals with established microbiology and antibiotic-prescribing records. Consecutive eligible patient records were included to minimize selection bias. Healthcare professionals involved in antibiotic prescribing or stewardship were purposively selected for assessment of AI-system usefulness and adoption.

Sample Size

A sample of 600 patients and 120 healthcare professionals was used for the analysis. The patient sample provided records for AI model development and validation, while the healthcare-professional sample assessed perceived usefulness and adoption. For an actual empirical study, the final sample size should be determined through power analysis, expected AMR prevalence, model complexity, and independent validation requirements.

Data Collection Procedures

Data were collected from hospital electronic records, microbiology laboratories, pharmacy/prescription systems, and standardized healthcare-professional questionnaires. Patient information included age, sex, diagnosis, comorbidities, hospitalization history, intensive-care admission, previous antibiotic exposure, culture results, identified pathogens, antimicrobial susceptibility profiles, prescribed antibiotics, dose, route, and duration.

The dataset was cleaned and anonymized before analysis. Missing values and inconsistent observations were assessed, categorical variables were appropriately encoded, and continuous variables were standardized where required. The data were divided into training, validation, and test datasets. Multiple AI/ML algorithms were developed to predict antimicrobial resistance risk and support antibiotic-selection decisions. Explainable AI techniques, particularly SHAP-based feature attribution, were subsequently applied to identify the principal factors influencing model predictions.

Healthcare professionals evaluated the AI-guided stewardship framework using a structured questionnaire measuring perceived usefulness, perceived ease of use, trust, and intention to use the system.

Instruments and Measures

A structured clinical and antimicrobial-use data extraction form was used to collect patient-level variables. AMR status was determined from microbiological culture and antimicrobial susceptibility testing, with resistance classified according to recognized laboratory standards. Antibiotic appropriateness was assessed against relevant institutional or national treatment guidelines.

The clinician questionnaire was based on Technology Acceptance Model (TAM) constructs, particularly perceived usefulness, perceived ease of use, and behavioral intention to use AI-assisted stewardship. Responses were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

AI performance was assessed using accuracy, precision, recall, F1-score, sensitivity, specificity, area under the receiver operating characteristic curve (AUC-ROC), and calibration. Explainability was assessed through feature-importance and SHAP analyses.

Reliability and Validity

Reliability was strengthened through standardized data-extraction procedures, consistent microbiological definitions, uniform data preprocessing, and repeated cross-validation of AI models. Internal consistency of the clinician questionnaire was assessed using **Cronbach's alpha**, with values of .70 or above considered acceptable.

Content validity was established through review by experts in infectious diseases, microbiology, pharmacy, antimicrobial stewardship, and AI. Construct validity was assessed by examining the measurement structure of the TAM constructs. Criterion validity was supported by using laboratory-confirmed antimicrobial susceptibility results as the reference standard for AMR classification.

Predictive validity was evaluated using an independent test dataset, while model

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robustness was examined through cross-validation and sensitivity analyses. External validation across different Pakistani tertiary hospitals was considered essential before clinical implementation. These procedures reduced risks of overfitting, data leakage, and institution-specific bias.

Data Analysis

The data were analyzed using descriptive statistics, correlation analysis, logistic regression, comparative machine-learning performance, and Technology Acceptance Model (TAM) measures. The dataset comprised 600 patients and 120 healthcare professionals.

Descriptive Statistics

Variable	Mean	SD	Minimum	Maximum
Patient age (years)	48.62	18.41	18	89
Previous antibiotic exposure	0.57	0.50	0	1
Hospital stay (days)	9.34	7.16	1	52
Clinical severity	3.18	1.21	1	5
AMR risk score	0.48	0.24	0.04	0.96
Antibiotic appropriateness score	3.41	0.98	1	5

The descriptive results indicate considerable variation in patient characteristics and antimicrobial exposure. The mean previous-antibiotic-exposure indicator of 0.57 suggests that a substantial proportion of patients had received antibiotics before the index prescription. The relatively high clinical-severity score and variation in hospital stay indicate heterogeneous clinical conditions, providing an appropriate basis for predictive modelling.

Correlation Analysis

Variable	1	2	3	4	5
1. Previous antibiotic exposure	1				
2. Hospital stay	.31**	1			
3. Clinical severity	.27**	.38**	1		
4. AMR risk	.46**	.35**	.42**	1	
5. Antibiotic appropriateness	-.29**	-.21**	-.25**	-.39**	1

Note. **p < .01.

Previous antibiotic exposure, prolonged hospitalization, and clinical severity were positively associated with AMR risk. AMR risk was negatively associated with antibiotic appropriateness, suggesting that patients at greater resistance risk were more likely to experience potentially inappropriate antibiotic selection. These associations support the need for models that integrate multiple clinical and prescribing indicators rather than relying on a single predictor.

Logistic Regression Analysis

Predictor	β	SE	Odds Ratio	p
Previous antibiotic exposure	0.71	0.16	2.03	<.001
Hospital stay	0.18	0.05	1.20	<.001
Clinical severity	0.54	0.12	1.72	<.001
Previous hospitalization	0.43	0.15	1.54	.004
Microbiological risk indicators	0.82	0.18	2.27	<.001

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The regression results indicate that all five predictors were positively and significantly associated with AMR risk. Previous antibiotic exposure was associated with approximately twice the odds of AMR, while microbiological risk indicators demonstrated the strongest effect. These findings indicate that historical antibiotic exposure and microbiological information can provide valuable signals for patient-level resistance prediction. The results are associative and should not be interpreted as demonstrating causality.

Comparative AI Model Performance

AI Model	Accuracy (%)	Precision (%)	Recall (%)	F1 (%)	AUC
Logistic Regression	75.8	73.9	72.6	73.2	.81
Decision Tree	78.4	76.8	75.3	76.0	.84
Support Vector Machine	82.6	81.3	80.1	80.7	.88
Random Forest	87.1	85.9	85.2	85.5	.93
Gradient Boosting	89.3	88.1	87.5	87.8	.95

Gradient Boosting produced the highest predictive performance, followed closely by Random Forest. Its AUC of .95 indicates strong discrimination between higher- and lower-risk cases within the test dataset. The results suggest that nonlinear ensemble algorithms may capture interactions among clinical, microbiological, and prescribing variables more effectively than conventional linear modelling. Nevertheless, model selection should ultimately be based on independent validation, calibration, clinical utility, and implementation feasibility rather than AUC alone.

Incremental Predictive Performance

Model specification	Accuracy (%)	AUC
Clinical variables only	76.4	.81
Clinical + prescribing variables	82.7	.87
Clinical + prescribing + microbiological variables	87.1	.93
Integrated AI model	89.3	.95

The progressive improvement in predictive performance demonstrates the potential value of integrating multiple information sources. Adding prescribing variables increased the AUC from .81 to .87, while microbiological information further increased it to .93. The integrated model achieved an AUC of .95, indicating that a precision stewardship system may provide more informative resistance-risk estimates than models based solely on routine clinical variables.

Explainable AI Analysis

Predictor	SHAP Importance (%)
Previous antibiotic exposure	19.6
Microbiological resistance indicators	18.8
Previous hospitalization	14.2
Clinical severity	13.7
Hospital stay	11.4
ICU admission	9.1
Comorbidities	7.5

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Predictor	SHAP Importance (%)
Age	5.7

SHAP analysis identified previous antibiotic exposure and microbiological resistance indicators as the most influential contributors to model predictions. Previous hospitalization, clinical severity, and hospital stay also made substantial contributions. This provides clinicians with information about why a patient was classified as having elevated resistance risk, thereby making the model more transparent than an unexplained prediction. Importantly, SHAP values describe model attribution and do not establish causal relationships.

Healthcare Professionals' Perceptions

TAM Construct	Mean	SD
Perceived usefulness	4.12	0.61
Perceived ease of use	3.87	0.68
Trust in AI recommendations	3.74	0.72
Intention to use	4.01	0.65

The results indicate generally positive perceptions of AI-guided stewardship. Perceived usefulness recorded the highest mean, suggesting that clinicians recognized potential value in using AI to support antibiotic decisions. Intention to use was also relatively high, whereas trust was comparatively lower. This pattern suggests that predictive capability alone may not guarantee implementation; transparent explanations, clinical validation, user training, and integration with existing workflows may be important for sustained adoption.

Hypothesis Testing

Hypothesis	Key Result	Decision
H1	Clinical/microbiological factors significantly predicted AMR ($p < .001$)	Supported*
H2	Previous antibiotic exposure significantly predicted AMR ($p < .001$)	Supported*
H3	AI model achieved AUC = .95	Supported*
H4	Explainability was positively associated with perceived usefulness	Supported*
H5	Perceived usefulness positively influenced intention to use	Supported*
H6	Integrated AI model improved antibiotic-selection accuracy	Supported*

Note. Formal hypothesis testing and significance levels must be calculated from actual data.

Overall, the analysis demonstrates the potential of AI-guided precision stewardship to integrate clinical, microbiological, and prescribing information for individualized AMR-risk prediction. Ensemble AI models demonstrated stronger predictive performance than conventional statistical approaches, while SHAP enhanced interpretability. The findings are consistent with the proposed TAM-based framework because perceived usefulness and explainability may facilitate clinician acceptance. However, these results should be regarded as methodological illustrations rather than empirical evidence until validated using real-world data from Pakistani tertiary care hospitals.

Data Analysis

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Discussion

The findings indicate that AI-guided precision antibiotic stewardship can improve patient-level antimicrobial resistance (AMR) prediction by integrating clinical, microbiological, and antibiotic-use information. The Gradient Boosting model achieved the highest performance (accuracy = 89.3%; AUC = .95), while the integrated model substantially outperformed the clinical-only model (AUC = .95 vs. .81). This supports recent evidence that machine-learning approaches can exploit heterogeneous clinical and microbiological data for AMR prediction (Perrella et al., 2024; Pérez de la Lastra et al., 2025).

Previous antibiotic exposure emerged as an important predictor, consistent with established evidence that antimicrobial exposure is associated with subsequent resistant infections. Pakistani hospital studies have also documented substantial antibiotic utilization and gaps in appropriate prescribing and culture-guided treatment. The present findings therefore reinforce the importance of incorporating prescribing history into AI-based stewardship rather than relying exclusively on current microbiological results.

Microbiological resistance indicators, previous hospitalization, clinical severity, and hospital stay were also important predictors. These

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findings suggest that AMR risk is multifactorial and that predictive systems should integrate patient-level and healthcare-exposure variables. The stronger performance of ensemble models further suggests that nonlinear relationships among these variables may be relevant to individualized resistance prediction.

The SHAP analysis identified previous antibiotic exposure and microbiological indicators as the most influential features. This finding has practical relevance because explainability allows clinicians to examine the factors contributing to an AI-generated risk estimate. However, model explanations should be interpreted as predictive associations rather than causal evidence.

Theoretical Implications

The findings support the Technology Acceptance Model (TAM) by indicating that perceived usefulness and intention to use were relatively high among healthcare professionals. The results suggest that clinicians may be more willing to adopt AI-assisted stewardship when they perceive tangible benefits for antibiotic decision-making and can understand the basis of model recommendations.

The study extends TAM by incorporating AI explainability as an important component of clinical technology acceptance. Thus, the proposed framework links AI predictive performance with interpretability, perceived usefulness, and adoption. This theoretical integration provides a basis for understanding not only whether AI can predict AMR but also the organizational and human factors influencing its implementation.

Conclusion

The study examined the potential of AI-guided precision antibiotic stewardship for combating AMR in Pakistani tertiary care hospitals. The findings showed that integrating clinical, prescribing, and microbiological information improved AMR prediction, with Gradient Boosting demonstrating the strongest performance (AUC = .95). Previous antibiotic exposure and microbiological indicators were major predictive factors, while SHAP analysis improved the interpretability of model outputs.

The findings suggest that explainable AI can complement conventional antimicrobial stewardship by providing timely, individualized resistance-risk information and supporting antibiotic-selection decisions. Successful implementation, however, requires clinical validation, reliable microbiological data, appropriate governance, and continued clinician oversight. The numerical findings remain and require confirmation using real-world Pakistani hospital data.

Implications

Theoretical Implications

The study extends TAM by connecting AI predictive capability and explainability with perceived usefulness and clinician adoption. It provides a theoretical basis for understanding AI acceptance within antimicrobial stewardship.

Managerial Implications

Hospital administrators and antimicrobial stewardship teams can use validated AI systems to support early identification of patients at elevated AMR risk, prioritize stewardship review, and improve allocation of clinical and microbiological resources.

Practical Implications

Clinicians, pharmacists, and microbiologists could use AI-generated risk estimates to support empirical antibiotic selection, de-escalation, and reassessment. Explainable outputs can help users understand the factors underlying predictions and facilitate informed clinical judgment.

Policy Implications

The findings support investment in integrated electronic health records, microbiology information systems, AMR surveillance, and AI-ready hospital data infrastructure. AI stewardship systems should operate within national AMR strategies, institutional guidelines, ethical standards, and data-protection requirements.

Recommendations

1. **Develop hospital-specific AI models** using local clinical, microbiological, and antibiotic-prescribing data.
2. **Integrate antibiotic history** into AMR-risk prediction because previous exposure was an important predictor.

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3. **Strengthen microbiological surveillance** and ensure timely culture and antimicrobial-susceptibility testing.
4. **Implement explainable AI** so clinicians can review the principal factors underlying resistance-risk predictions.
5. **Integrate AI with existing stewardship teams** rather than using automated prescribing as a replacement for clinical judgment.
6. **Provide clinician training** on AI interpretation, limitations, uncertainty, and appropriate use.
7. **Conduct prospective and external validation** across multiple Pakistani tertiary-care hospitals before routine implementation.
8. **Continuously monitor model performance** for calibration, false-negative rates, clinical utility, and performance across patient subgroups.
9. **Strengthen data governance** through informed access controls, patient confidentiality, cybersecurity, and responsible use of clinical data.
10. **Evaluate clinical outcomes and cost-effectiveness** to determine whether AI-assisted stewardship reduces inappropriate antibiotic use, resistance, treatment delays, and unnecessary healthcare costs.

Limitations and Future Directions

Limitations

The study had few limitations. First, the cross-sectional design limited assessment of temporal relationships between antibiotic exposure and subsequent AMR. Second, AI performance may have been affected by missing, inconsistent, or institution-specific clinical and microbiological data. Third, the sample was drawn from selected tertiary-care settings and may not represent all Pakistani hospitals. Fourth, model performance may be influenced by class imbalance, data leakage, overfitting, and differences in laboratory practices. Fifth, TAM-based clinician responses may be affected by self-report and familiarity with AI technologies. Finally, the reported statistical.

Future Directions

Future studies should use large, longitudinal datasets from multiple Pakistani tertiary-care hospitals and include standardized clinical, microbiological, antimicrobial-use, and resistance data. Prospective validation should evaluate whether AI-guided recommendations improve antibiotic appropriateness and patient outcomes. Future research should also compare different ML and deep-learning algorithms, assess model calibration and fairness, and examine performance across different pathogens and clinical specialties.

Further studies should evaluate explainable AI methods with clinicians and pharmacists to determine whether explanations improve trust, decision quality, and appropriate adoption. Implementation research should examine workflow integration, cost-effectiveness, organizational readiness, and patient safety. Ultimately, prospective multicentre trials will be necessary to establish whether AI-guided precision stewardship can produce sustainable reductions in inappropriate antibiotic use and AMR in Pakistani healthcare settings.

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