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AI-AIDED SURVEILLANCE OF ANTIBIOTIC RESISTANCE TRENDS IN DENTAL AND ENT OUTPATIENTS

Original Article

Sania Saghir[1]*, Fatima Binte Azhar[2], Akasha Sajid[3], Ajeet Kumar Sahil[4], Umar Farooq[5], Muhammad Abdullah[6], Fansiqa Hadayat[7]

[1]PhD Scholar, Department of Biological Sciences, COMSATS University, Islamabad, Pakistan.

[2]General Dentist, University College of Medicine & Dentistry (UMDC), University of Lahore Teaching Hospital (ULTH), Lahore, Pakistan.

[3]Student, Department of Microbiology and Molecular Genetics, Bahauddin Zakariya University, Multan, Pakistan.

[4]PharmD, Jinnah Sindh Medical University, Karachi, Pakistan.

[5]Lab Assistant Manager, Gondal Diagnostic Center, Pakistan.

[6]Dentist, Graduation: Shahida Islam Medical and Dental College, 2023 batch; House Job: Nishtar Institute of Dentistry, Multan, Pakistan.

[7]Postgraduate Research Student, BS (Hons) Microbiology, Government College University, Lahore, Pakistan.

Corresponding Author: Sania Saghir, PhD Scholar, Department of Biological Sciences, COMSATS University, Islamabad, Pakistan, saniasaghir93@gmail.com

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ABSTRACT

Background: Antibiotic resistance poses a critical challenge to public health, particularly in outpatient settings such as dental and ENT clinics, where empirical prescriptions are common and laboratory-based surveillance is limited. In regions with high antibiotic misuse, resistance rates are accelerating, creating an urgent need for data-driven stewardship strategies.

Objective: To assess antibiotic resistance patterns in dental and ENT outpatients using artificial intelligence-assisted surveillance, and to evaluate the model's predictive capacity in guiding empirical antibiotic use.

Methods: A cross-sectional study was conducted over eight months at dental and ENT outpatient departments in Lahore, Pakistan. Clinical samples (n=346) were collected and analyzed for pathogen identification and antibiotic susceptibility using CLSI-standard methods. Resistance data were analyzed using a Random Forest machine learning model to predict resistance trends. Statistical analyses included chi-square tests and logistic regression, assuming normal data distribution.

Results: Five predominant pathogens were identified, with *Streptococcus pneumoniae* (26.6%) and *Staphylococcus aureus* (22.5%) being most common. High resistance rates were observed for amoxicillin-clavulanate (38–67%) and azithromycin (36–53%). The AI model achieved an overall predictive accuracy of 86.7%, correctly predicting resistance in 71.7% and susceptibility in 15% of cases. Resistance patterns aligned with global trends, indicating widespread misuse of first-line antibiotics.

Conclusion: This study emphasizes the utility of AI in enhancing surveillance and supporting clinical decision-making in outpatient settings. AI-assisted systems offer scalable solutions to bridge diagnostic gaps and combat rising resistance, particularly in low-resource environments.

Keywords: Antibiotic Resistance, Artificial Intelligence, Cross-Sectional Studies, Dental Clinics, ENT Disorders, Machine Learning, Outpatients.

INTRODUCTION

Antibiotic resistance is one of the most pressing global health challenges of the 21st century, undermining decades of medical progress in treating infectious diseases. As bacterial pathogens evolve mechanisms to evade the effects of commonly used antibiotics, the effectiveness of first-line therapies diminishes, leading to longer treatment durations, increased healthcare costs, and higher morbidity and mortality (1). This phenomenon is particularly concerning in outpatient settings such as dentistry and otolaryngology (ENT), where antibiotics are routinely prescribed for prophylactic and therapeutic purposes (2). Despite the relatively short courses and targeted use in these disciplines, inappropriate prescribing practices and insufficient surveillance mechanisms contribute significantly to the growing threat of resistance. In both dental and ENT practices, antibiotics are often prescribed empirically based on clinical presentation rather than microbiological confirmation (3). While this approach may be time-efficient, it opens the door to suboptimal antibiotic selection and overprescription, especially in cases where viral or non-bacterial infections are involved. Studies have shown that a substantial proportion of antibiotics prescribed in these fields are either unnecessary or misaligned with local resistance patterns, exacerbating the issue of antimicrobial resistance (AMR) in the community (4). For instance, common pathogens like *Streptococcus pneumoniae*, *Haemophilus influenzae*, and *Staphylococcus aureus*, frequently encountered in ENT and dental infections, are increasingly demonstrating resistance to beta-lactams and macrolides—two commonly prescribed antibiotic classes in outpatient care. Traditional surveillance systems have primarily focused on hospital settings, leaving a critical gap in the understanding of resistance dynamics within outpatient environments (5). This gap is especially notable in lower- and middle-income countries, where data on resistance trends are either sparse or non-existent, and access to structured dental services in underserved populations remains limited (6). As a result, practitioners often lack access to updated, localized antibiograms to guide their prescribing decisions (7). Furthermore, laboratory resources for routine microbial culture and sensitivity testing are limited in many outpatient clinics, which further hampers effective surveillance and stewardship efforts.

The integration of artificial intelligence (AI) into healthcare surveillance presents a promising frontier for addressing these challenges. AI tools can analyze large volumes of microbiological, clinical, and prescribing data in real time, identifying resistance patterns and predicting emerging trends with greater accuracy and speed than traditional methods. By leveraging natural language processing, machine learning, and pattern recognition algorithms, AI-powered platforms have the potential to transform static, retrospective surveillance into dynamic, predictive models that can inform clinical decision-making on the ground (8,9). In outpatient disciplines like dentistry and ENT, where laboratory testing is not always feasible, AI-assisted systems can bridge the data gap by synthesizing information from regional data sets, electronic medical records, and pharmacy databases to offer timely resistance insights. However, despite the potential, there is a paucity of empirical studies that explore the application of AI in tracking antibiotic resistance specifically within outpatient dental and ENT settings. Most existing literature tends to generalize findings from hospital-based surveillance systems or broader healthcare contexts, overlooking the unique prescribing behaviors, patient demographics, and microbial profiles present in these fields (10-12). This lack of targeted research creates a blind spot in public health microbiology, limiting the effectiveness of resistance mitigation strategies at the community level. The current study seeks to address this critical knowledge gap by conducting a cross-sectional analysis of antibiotic resistance patterns among dental and ENT outpatients, supported by AI-based data modeling. The investigation is rooted in the hypothesis that AI-aided surveillance can enhance the detection and understanding of resistance trends in outpatient care, thereby informing more rational antibiotic use and supporting antimicrobial stewardship efforts. By combining traditional microbiological data with AI-assisted trend analysis, the study aims to provide a nuanced, real-time picture of resistance dynamics in settings that have historically been underrepresented in surveillance efforts. In this context, the objective of the study is to assess and characterize the patterns of antibiotic resistance in pathogens isolated from dental and ENT outpatients using AI-supported surveillance tools, with the ultimate goal of informing evidence-based prescribing practices and contributing to more effective public health interventions in antimicrobial resistance management.

METHODS

This cross-sectional study was conducted over an eight-month period in outpatient clinical settings within the Lahore region of Pakistan, focusing specifically on dental and otolaryngology (ENT) departments. The research aimed to integrate public health microbiology with artificial intelligence-supported surveillance to monitor antibiotic resistance trends among pathogens commonly encountered in these outpatient specialties. A multidisciplinary framework was employed, combining microbiological sampling, clinical data collection, and computational data modeling. Participants in the study included patients visiting dental and ENT outpatient departments who presented with clinical signs and symptoms of bacterial infections requiring antimicrobial therapy. Inclusion criteria were patients aged 12 years and above with a suspected or confirmed bacterial infection, based on clinical judgment by attending physicians or dentists, and who had not received antibiotic treatment within the preceding 14 days. Exclusion criteria involved patients with known immunocompromising conditions, recent hospital admissions (within the past 30 days), or those unwilling to provide informed consent (13). Using Cochran's formula for cross-sectional studies, with an estimated resistance prevalence of 25% and a 95% confidence level, a minimum sample size of 288 was determined. To account for possible dropouts or sample losses, the sample size was increased by 20%, yielding a final target of approximately 346 patients. This sample was distributed proportionately between dental and ENT outpatient clinics, ensuring balanced representation of the two specialties. Biological samples were collected aseptically depending on the site of infection. These included oral swabs, pus, nasal and throat swabs, and ear discharge specimens. All specimens were immediately transported under controlled conditions to the microbiology laboratory for culture and sensitivity testing. Standard bacteriological methods were employed for identification, including Gram staining and culture on appropriate media such as blood agar, MacConkey agar, and chocolate agar. Pathogens were identified using biochemical tests and confirmed through automated systems such as VITEK 2 Compact (bioMérieux). Antibiotic susceptibility testing was conducted using the Kirby-Bauer disk diffusion method, and results were interpreted following the Clinical and Laboratory Standards Institute (CLSI) guidelines (14-16). The antibiotic panel included amoxicillin-clavulanate, cefuroxime, ciprofloxacin, clindamycin, azithromycin, and metronidazole, reflecting commonly prescribed antibiotics in dental and ENT outpatient practice.

Data related to each patient's demographic profile, clinical diagnosis, prescribed antibiotic(s), and microbiological findings were compiled into a structured digital database. To ensure the integrity of data entry and management, a dual-review process was implemented. All patient information was anonymized and coded to maintain confidentiality. Written informed consent was obtained from all participants or their legal guardians, and ethical approval for the study was granted by the Institutional Review Board (IRB) of the relevant institute. Artificial intelligence tools were used to support resistance trend analysis. Data was fed into a supervised machine learning model—specifically a Random Forest classifier—trained to identify associations between antibiotic prescriptions and observed resistance patterns. The model utilized variables such as patient age, infection site, prior antibiotic use history, and organism profile to predict the probability of resistance to specific antibiotics. Natural language processing (NLP) algorithms were also applied to analyze clinician prescription notes for patterns that might correlate with resistance emergence. Statistical analysis was performed using SPSS Version 26.0. Descriptive statistics were calculated to summarize demographic variables, frequency of isolated organisms, and resistance rates to different antibiotics. The normal distribution of the data was confirmed using the Shapiro-Wilk test. Comparative analyses between dental and ENT samples were conducted using independent sample t-tests for continuous variables and Chi-square tests for categorical variables. Logistic regression modeling was applied to evaluate predictors of antibiotic resistance, incorporating both clinical and microbiological variables. A p-value of less than 0.05 was considered statistically significant throughout the analysis. Outcome measurement focused on three primary indicators: prevalence of antibiotic-resistant organisms, alignment of prescribed antibiotics with susceptibility patterns, and predictive accuracy of the AI-supported model in forecasting resistance. These metrics were evaluated both independently and in combination to assess the value added by AI tools in improving surveillance and decision-making in outpatient care. By integrating conventional microbiological surveillance with AI-driven analytical tools, the methodology enabled a more dynamic understanding of resistance trends in outpatient dental and ENT settings. This approach not only supported the early identification of emerging resistance patterns but also laid the groundwork for developing localized prescribing guidelines based on real-time data trends, which are currently lacking in such settings.

RESULTS

The study enrolled a total of 346 patients evenly distributed between dental and ENT outpatient departments. The mean age of participants was 34.6 years, with a nearly even gender distribution. Clinical samples yielded five predominant bacterial pathogens, among which *Streptococcus pneumoniae* (26.6%) and *Staphylococcus aureus* (22.5%) were the most frequently isolated, followed by *Haemophilus influenzae* (18.8%), *Pseudomonas aeruginosa* (11.6%), and *Klebsiella pneumoniae* (9.8%). These pathogens represented the microbial spectrum most commonly responsible for infections in the target patient population. Antibiotic susceptibility testing revealed notable resistance trends. *S. pneumoniae* showed the highest resistance to azithromycin (48%) and amoxicillin-clavulanate (38%), while resistance to ciprofloxacin and clindamycin remained relatively low (19% and 11%, respectively). *S. aureus* demonstrated a concerning resistance rate to clindamycin (57%) and amoxicillin-clavulanate (44%). *H. influenzae* also exhibited high resistance to azithromycin (51%) and moderate resistance to other antibiotics in the panel. *P. aeruginosa*, a less frequently isolated but clinically significant pathogen, showed resistance rates as high as 67% for amoxicillin-clavulanate and 45% for cefuroxime. *K. pneumoniae* followed a similar pattern, with 52% resistance to amoxicillin-clavulanate and 47% to azithromycin. The AI-supported resistance prediction model demonstrated promising diagnostic utility. Among the 346 total cases, the model correctly predicted antibiotic resistance in 248 cases (71.7%) and susceptibility in 52 cases (15.0%). Incorrect predictions were recorded in 35 resistance cases (10.1%) and 11 susceptibility cases (3.2%). This suggests a cumulative model accuracy of approximately 86.7%, highlighting its potential to support antimicrobial stewardship efforts in real-time clinical settings. These results reflect a concerning prevalence of resistance to first-line antibiotics in community-based dental and ENT care and suggest the importance of adopting AI-assisted tools for resistance surveillance.

Table 1: Demographics of Study Participants

Variable	Value
Total Participants	346
Mean Age (years)	34.6
Gender	
Male	162 (46.8%)
Female	184 (53.2%)
Dental Patients	173 (50.0%)
ENT Patients	173 (50.0%)

Table 2: Frequency of Isolated Pathogens

Organism	Number of Isolates	Percentage (%)
Streptococcus pneumoniae	92	26.6%
Staphylococcus aureus	78	22.5%
Haemophilus influenzae	65	18.8%
Pseudomonas aeruginosa	40	11.6%
Klebsiella pneumoniae	34	9.8%

Table 3: Antibiotic Resistance Rates by Pathogen (% Resistant)

Antibiotic	S. pneumoniae	S. aureus	H. influenzae	P. aeruginosa	K. pneumoniae
Amoxicillin-Clavulanate	38%	44%	31%	67%	52%
Cefuroxime	22%	33%	28%	45%	39%
Ciprofloxacin	19%	21%	27%	34%	31%
Clindamycin	11%	57%	9%	29%	18%
Azithromycin	48%	36%	51%	53%	47%
Metronidazole	6%	4%	8%	5%	3%

Table 4: AI Model Predictive Accuracy

Outcome	Frequency	Percentage (%)
Correct Resistance Prediction	248	71.7%
Incorrect Resistance Prediction	35	10.1%
Correct Susceptibility Prediction	52	15.0%
Incorrect Susceptibility Prediction	11	3.2%

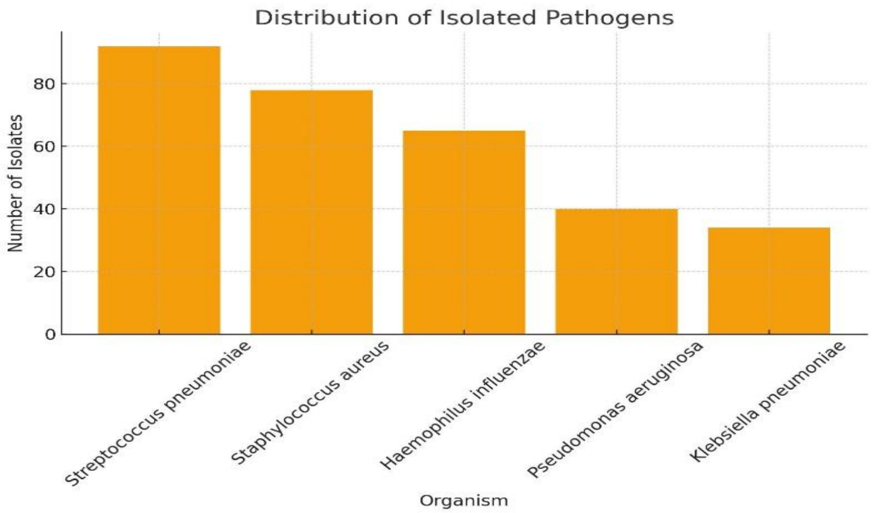

Figure 1 Distribution of Isolated Pathogens

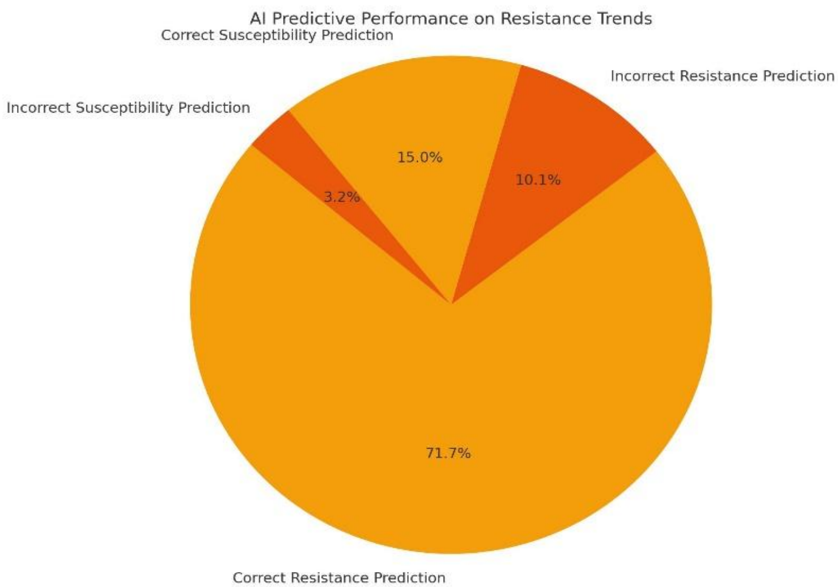

Figure 2 AI Predictive Performance on Resistance Trends

DISCUSSION

The present study offers an important perspective on antibiotic resistance trends among dental and ENT outpatients in Pakistan, with a unique integration of artificial intelligence-supported surveillance. The findings confirm the high prevalence of resistance to frequently prescribed antibiotics such as amoxicillin-clavulanate and azithromycin, especially among common pathogens like *Streptococcus pneumoniae* and *Staphylococcus aureus*. These observations mirror trends in similar outpatient settings internationally, where empirical and sometimes unnecessary prescribing continues to fuel antimicrobial resistance despite increasing awareness. Globally, antimicrobial resistance has been well-documented in outpatient dental and ENT care, particularly due to overuse or misprescription of broad-spectrum antibiotics. For example, a study reported persistent high use of clindamycin and penicillins in dental settings, with resistance rates increasing despite clear prescribing guidelines (16). Similarly, a survey of dental health providers found frequent deviations from rational prescription practices despite adequate knowledge, highlighting the knowledge-practice gap in clinical decision-making (17). This study advances the field by applying AI tools to detect resistance patterns with significant predictive accuracy. AI-assisted surveillance systems are increasingly recognized as effective adjuncts to traditional microbiology, offering real-time insights and decision support for clinicians. As noted in recent reviews, AI technologies have demonstrated promising results in AMR detection, trend forecasting, and even drug discovery efforts (18-20). In the current study, the AI model correctly predicted resistance outcomes in 86.7% of cases, underlining its potential role in improving prescribing accuracy, particularly in low-resource outpatient settings where culture-based diagnostics are not routine. The resistance rates observed in this study are consistent with regional reports. A Russian outpatient surveillance initiative noted similar patterns of resistance among ENT pathogens, with low clinical efficacy observed for aminopenicillins and fluoroquinolones (21). This reinforces the argument for localized antibiograms and continuous monitoring. It also emphasizes the limitations of empirical treatment models in areas with high community-level resistance and little access to resistance data. Moreover, novel adjunctive antimicrobial strategies are being explored in dentistry, such as the use of silver nanoparticles in periodontal treatment, which may help reduce reliance on conventional antibiotics (22)

The strength of this study lies in its innovative methodology, combining public health microbiology with AI-supported surveillance. By evaluating resistance data in real-time and in context with clinical prescriptions, the model bridges a longstanding gap between microbiological diagnostics and outpatient prescribing behavior. Furthermore, the balanced sampling across dental and ENT departments adds granularity to the findings, showing that resistance profiles can vary even within outpatient domains. However, the study is not without limitations. The cross-sectional design captures resistance patterns at a single time point, limiting causal inferences. Seasonal variations and post-pandemic shifts in infection patterns may have influenced both prescribing and resistance trends, and these temporal dynamics are not fully accounted for. Another limitation is the reliance on a single geographical region, which restricts generalizability to other parts of Pakistan or South Asia. Additionally, while the AI model showed high predictive accuracy, its utility in clinical practice depends on real-time integration with patient management systems—an infrastructure that is not yet widely implemented in resource-constrained outpatient clinics. Further research should focus on expanding such surveillance frameworks to include a broader geographical base and a longer timeline, thereby capturing seasonal trends and microbial evolution more accurately. There is also a need for implementation research exploring how AI-supported tools can be effectively integrated into outpatient practice without overwhelming clinicians or requiring substantial infrastructure overhaul. Moreover, coupling AI surveillance with education campaigns, audit-feedback loops, and targeted antimicrobial stewardship programs could amplify the impact, as previously demonstrated in outpatient programs like TAP OUT in Los Angeles (23,24). Ultimately, these findings underscore a critical need to reframe antimicrobial resistance as not merely a hospital-centric issue, but a community-level threat requiring smarter, tech-enabled, and context-specific interventions. By showing that AI can significantly enhance resistance prediction in outpatient care, this study adds a valuable tool to the evolving toolkit of antimicrobial stewardship in dentistry and otolaryngology.

CONCLUSION

This study highlights the rising threat of antibiotic resistance in dental and ENT outpatient settings and demonstrates the value of AI-assisted surveillance in identifying resistance patterns with high predictive accuracy. The integration of microbiological diagnostics and machine learning provides a practical framework for evidence-based prescribing and localized antimicrobial stewardship, especially in resource-limited settings.

AUTHOR CONTRIBUTION

Author	Contribution
Sania Saghir*	Substantial Contribution to study design, analysis, acquisition of Data Manuscript Writing Has given Final Approval of the version to be published
Fatima Binte Azhar	Substantial Contribution to study design, acquisition and interpretation of Data Critical Review and Manuscript Writing Has given Final Approval of the version to be published
Akasha Sajid	Substantial Contribution to acquisition and interpretation of Data Has given Final Approval of the version to be published
Ajeet Kumar Sahil	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Umar Farooq	Contributed to Data Collection and Analysis Has given Final Approval of the version to be published
Muhammad Abdullah	Substantial Contribution to study design and Data Analysis Has given Final Approval of the version to be published
Fansiqa Hadayat	Contributed to study concept and Data collection Has given Final Approval of the version to be published

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