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Knowledge, Practices and Behavioral Predictors of Antimicrobial Resistance Among University Students in Uganda: A Non-parametric and Machine Learning Analysis with Regional Insights for East Africa

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Abstract

This study evaluates AMR-related knowledge, practices and behavioral predictors among university students in Uganda using a mixed-method approach combining descriptive statistics, non-parametric analysis and machine learning. A cross-sectional online survey (n=123) was conducted among students of Uganda. Results revealed high AMR awareness (76.4% had heard of AMR; 85.4% aware of dosage risks), yet inconsistent practices persisted, with 35.8% self-medicating and 32.5% sharing antibiotics. Logistic regression and CatBoost classifier analysis identified belief in AMR severity, field of study, gender and perceived cost as the most significant behavioral predictors. Younger students and non-medical students were more likely to exhibit non-compliant behaviors. K-Means clustering and Principal Component Analysis (PCA) revealed three behavior profiles—Compliant, At Risk and Unaware—demonstrating the utility of machine learning for behavioral segmentation. The findings confirm a cognitive–behavioral disconnect, where knowledge does not guarantee safe antibiotic use and highlight the importance of integrating Health Belief Model (HBM) construct into AMR education. This study contributes methodologically by introducing a Behavioral Risk Profiling Framework and practically by informing tailored university-based interventions. Institutional strategies should include belief-targeted education, curriculum integration in non-medical programs and cost-reduction initiatives. The study underscores the need for precision public health models to promote antimicrobial stewardship among youth in resource-limited settings.

Keywords: Antimicrobial Resistance (AMR), Behavioral Predictors, Machine Learning, University Students.

Introduction

Antimicrobial resistance (AMR) is a major global public health threat, weakening the effectiveness of antibiotics and threatening clinical care, food security, economic stability and sustainable development. AMR is associated with approximately 4.95 million deaths annually and projections suggest that deaths could rise substantially by 2050 if current trends continue (1). The economic burden is also considerable, with global costs estimated at USD 100–150 billion annually and projected to increase further by 2030 (2). The misuse and overuse of antibiotics in human medicine, agriculture and livestock production remain key drivers of resistance, particularly in low- and middle-income countries (LMICs), where unregulated access, weak health systems, limited diagnostics and poor public awareness intensify the problem (1, 2). Addressing AMR requires a One Health approach that integrates human, animal and environmental health, alongside surveillance, antimicrobial stewardship, improved diagnostics, vaccines and investment in new antibiotics (3, 4). International policy frameworks, including the World Health Organization's Global Action Plan on AMR, emphasize improving awareness and understanding through education, strengthening evidence through surveillance and research and optimizing antimicrobial use. These priorities are especially relevant in university settings, where young adults are both current healthcare consumers and future professionals whose knowledge, beliefs and antibiotic-use practices may influence broader antimicrobial stewardship. This study is guided by the Health Belief Model (HBM), which explains how health-related behavior is shaped by perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to

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action and self-efficacy (5). HBM is particularly useful for understanding antibiotic-use behavior because students may know about AMR but still self-medicate, share antibiotics, or fail to complete prescribed courses if they do not perceive AMR as personally relevant, severe, or preventable. Evidence from different settings shows that public misconceptions remain common: some individuals stop antibiotics when symptoms improve despite having basic awareness, while inappropriate prescribing, non-therapeutic antibiotic use in animals, misinformation and weak health-system access continue to drive resistance (6–9).

University students are an important group for AMR research and intervention. Their antibiotic-use behaviors are influenced not only by knowledge but also by psychological, social, institutional and economic factors. Limited trust in healthcare systems, negative perceptions of campus health services, discrimination, poor access to credible advice, peer influence and risky health behaviors can encourage self-medication or inappropriate antibiotic use (10–15). Educational interventions can improve AMR awareness, but they must address students' lived experiences, perceived barriers, self-efficacy and social contexts rather than relying only on information delivery (16).

In East Africa, AMR remains a serious and under-addressed challenge. Surveillance systems are limited, antimicrobial stewardship programs are inconsistently implemented and public knowledge remains uneven. Studies from the region show high levels of multidrug-resistant bacterial isolates, insufficient AMR knowledge among many populations and continued non-prescription antimicrobial access in both human and veterinary contexts (17–21). Socioeconomic inequality, poor sanitation, rural residency, educational disparities and weak health infrastructure further shape AMR risk and limit the uptake of prevention practices (22). Regional initiatives such as the HATUA project demonstrate the importance of localized, interdisciplinary research for understanding the social and biological drivers of resistance (23).

Most AMR studies among students rely on Knowledge, Attitude and Practice (KAP) approaches. Although useful, traditional descripttive KAP studies often do not fully explain why awareness fails to translate into safe antibiotic-use behavior. They may also miss hidden behavioral patterns across subgroups. Machine learning methods, including K-Means clustering, Principal Component Analysis (PCA) and CatBoost classification, can help identify latent behavioral profiles, assess predictors of non-compliance and support targeted intervention design (24). When combined with HBM, these methods can move AMR research beyond description toward behaviorally informed risk profiling.

Despite growing global attention to AMR, three gaps remain insufficiently addressed in the East African university context. First, limited evidence explains the awareness–practice gap among university students, particularly why students continue risky antibiotic-use behaviors despite knowing about AMR. Second, few studies operationalize behavioral theory, especially HBM constructs, to interpret antibiotic-use decisions among university students in Uganda and similar East African settings. Third, limited research combines non-parametric statistics and machine learning to identify predictors of risky antibiotic use and classify students into behavioral risk profiles. These gaps restrict the development of targeted, data-driven university interventions.

Therefore, this study assesses AMR-related knowledge, practices and behavioral patterns among surveyed university students in Uganda. Specifically, it seeks to:

(a) evaluate AMR awareness and antibiotic-use practices among the surveyed students;
(b) identify demographic and behavioral predictors associated with risky or non-compliant AMR-related behaviors within this sample; and
(c) explore the use of non-parametric statistical methods and machine learning models to classify students into AMR behavioral risk groups.

The findings are intended to inform context-specific educational and policy interventions, with cautious relevance to similar university settings in East Africa.

Behavioral change theories such as the Health Belief Model (HBM) is widely applied in addressing antimicrobial resistance (AMR), offering structured insights into how individuals assess risks and make decisions about preventive health behaviors. The HBM suggests that individuals are more likely to use antibiotics responsibly if they believe they are susceptible to AMR and that its consequences are severe (25). This model also emphasizes the role of perceived benefits and barriers, as well as cues to action such as educational materials and public campaigns in encouraging behavior change (26). Integrating this model allows AMR interventions to be more adaptable, culturally sensitive and behaviorally relevant (27).

Recent advances in machine learning (ML) have been instrumental in expanding public health research, including AMR-related behavior prediction. ML models have been used to forecast vaccine hesitancy and mental health trends (28, 29). In the AMR context, predictive analytics have enabled researchers to identify risk patterns, such as inappropriate antibiotic prescribing (24). These techniques go beyond traditional statistical methods by uncovering hidden relationships in behavioral data, classifying individuals into distinct risk groups and guiding targeted interventions based on supervised and unsupervised learning algorithms.

Studies examining AMR awareness among youth demonstrate both the potential and challenges of this demographic. In Tanzania, awareness among secondary school students rose from below 37% to over 90% following educational interventions (16). In Bangladesh, while youth showed average awareness, misconceptions—such as discontinuing antibiotics when symptoms subsided—persisted (6). Among Indian medical students, awareness was high, yet behaviors like self-medication were still prevalent (30, 31). Malaysian students showed high awareness but inconsistent practices (32), while 28.3% of Canadian university students admitted to using antibiotics without a prescription (33). Even minimal AMR knowledge has been linked to more responsible use (34). Campaigns like India's "Red Line" and Tanzania's youth-led AMR clubs illustrate the value of curriculum-based interventions and peer education (16, 35).

Sociocultural and structural factors also shape student behaviors. In LMICs, limited access to affordable healthcare and high out-of-pocket costs often lead to self-medication (36). Students who distrust healthcare institutions are more likely to seek informal advice or bypass prescriptions altogether (37). Peer influence and the desire to conform socially contribute to practices like sharing antibiotics or stopping treatment prematurely (11). These influences must be understood to design interventions that resonate within specific cultural and institutional settings.

In the African context, significant gaps exist in AMR education, surveillance and resources. Pharmacy and health curricula often lack sufficient content on antimicrobial use (AMU), AMR and stewardship (AMS), limiting students' preparedness (21). Access to learning tools is also low, with only 36% of healthcare students having AMR-related mobile apps, despite strong interest (38). While tools like the CwPAMS app offer promise, broader implementation is required. Many African countries lack national AMR surveillance systems, leading to data scarcity and policy delays (39). Inadequate regional studies and methodological inconsistencies further restrict curriculum development (40). Socio-ecological factors—such as poor sanitation, rural residency and low educational attainment—also drive AMR and must be integrated into education strategies (22). Although efforts like CwPAMS and HATUA represent progress, scaling them requires investment in infrastructure, curriculum reform and local research capacity.

Despite growing global attention to antimicrobial resistance (AMR), there remains a critical gap in understanding the knowledge, attitudes and practices (KAP) of university students in Africa—particularly in East Africa—who represent a key demographic in shaping future healthcare behaviors. While behavior change theories such as the Health Belief Model has been applied in AMR interventions, limited research explores how these frameworks can be operationalized among youth populations in African university settings. Existing studies show mixed levels of awareness and responsible behavior among students globally, yet there is a lack of region-specific, behaviorally informed data from African universities. Moreover, student-focused AMR literature in Africa reveals major deficiencies in educational curricula, technological resources and surveillance systems, which constrain both learning and effective stewardship. The underrepresentation of African student populations in AMR research and the absence of predictive modeling further limits the development of targeted, data-driven interventions. These gaps point to the need for studies that assess AMR awareness and behavior among East African university students, identify demographic and behavioral predictors of risky antibiotic use and utilize non-parametric and machine learning approaches to classify students into AMR risk profiles. Accordingly, this study is guided by the following research questions:

(a) What is the level of AMR awareness and practice among East African university students?
(b) Are there demographic or behavioral predictors of risky AMR-related behavior?
(c) Can machine learning models accurately classify students into behavioral risk groups to inform intervention strategies?

Methodology

Research Design

This study adopted a cross-sectional survey design, a widely used approach in public health research for assessing the prevalence of health-related knowledge, attitudes and practices (KAP) within a defined population at a specific point in time (6). The design enabled the researchers to explore the awareness and behaviors related to antimicrobial resistance (AMR) among university students in Uganda, while also identifying patterns that could inform predictive modeling.

Target Population and Sampling

The study focused on university students from Uganda. Participants were university students aged 18–35 years, primarily Ugandan nationals, drawn from two tertiary institutions: Kabale University, a government-funded public university (1°16′18.0″S, 29°58′18.0″E) and Kampala International University, a private institution (0°17′41.0″N, 32°36′13.0″E). Most respondents were enrolled in medical-related programs, reflecting the study's focus on AMR awareness and health-related behaviors. University students were selected because of their transitional role as emerging healthcare consumers and their unique susceptibility to misinformation and risky antibiotic use (10). Although this study was conducted among students from two universities in Uganda—Kabale University (a government-funded public institution) and Kampala International University (a private tertiary institution)—its conceptual framing adopts a regional lens. Uganda is part of the East African Community (EAC), a bloc of countries that share similar public health systems, tertiary education structures and AMR-related challenges. Therefore, while the data were collected within Uganda, the insights generated are intended to inform broader regional strategies. This framing aligns with ongoing WHO and Africa CDC efforts to promote regional coordination and knowledge-sharing in antimicrobial stewardship. As such, the study positions the two Ugandan universities as East African case sites that provide context-specific evidence from within the region. However, because the sample was limited to two institutions in Uganda and used convenience sampling, the findings should not be interpreted as statistically representative of all East African university students. Rather, they offer cautious, transferable insights for similar university settings in East Africa that share comparable public-health, educational and antimicrobial stewardship challenges.

A non-probability convenience sampling method was employed due to logistical constraints and the online nature of the survey. Invitations were distributed via institutional mailing lists and student groups on WhatsApp, with a total of 123 students completing the questionnaire. Inclusion criteria required that participants be currently enrolled in a recognized university in the East African region and provide informed consent.

Instrument Development and Theoretical Anchoring

The primary data collection tool was a structured, self-administered online questionnaire developed to evaluate participants' demographic characteristics, knowledge of antimicrobial resistance (AMR), antibiotic use behaviors and attitudes toward antimicrobial stewardship. This study is guided by the Health Belief Model (HBM), which provides a theoretical lens to understand antibiotic-related behaviors. HBM is adopted due to its emphasis on individual beliefs influencing health behavior (41). The instrument was therefore structured to reflect the six core constructs of the HBM:

a) **Perceived Susceptibility**: Measured through questions such as "Do you believe you are at risk of AMR if you misuse antibiotics?" and "Have you ever knowingly taken an antibiotic without a prescription?"
b) **Perceived Severity**: Captured by items like "Do you believe AMR is a serious health threat?" and "Do you think incomplete use of antibiotics could lead to drug-resistant infections?"

c) **Perceived Benefits**: Assessed via responses to questions about the perceived value of completing prescribed courses and consulting healthcare providers before antibiotic use.
d) **Perceived Barriers**: Evaluated through items addressing economic constraints (e.g., "I avoid going to the clinic due to cost") and accessibility (e.g., "It is difficult to see a doctor when I need antibiotics").
e) **Cues to Action**: Represented by questions asking if students had received information on AMR in class, media, or health campaigns, e.g., "Have you been educated on AMR at your university?"
f) **Self-efficacy**: Reflected in items probing confidence in adhering to antibiotic prescriptions, e.g., "How confident are you that you can always follow prescribed antibiotic instructions?"

These constructs were analyzed both descriptively and inferentially and later incorporated into the CatBoost and logistic regression models to determine their predictive power on AMR behavior. Mapping the HBM in this way allowed for a theoretically grounded interpretation of behavioral patterns and the design of segment-specific interventions (25, 42). In the analysis, risky antibiotic-use behaviors were interpreted through these HBM constructs. Self-medication was linked to perceived barriers, particularly cost and limited access to professional care. Antibiotic sharing and incomplete dosage were interpreted in relation to low perceived severity, weak perceived susceptibility and limited understanding of the benefits of completing prescribed treatment. Belief in AMR as a serious issue was treated as a proxy indicator of perceived threat, while prior AMR education and exposure to health information were interpreted as cues to action. This theoretical mapping allowed the study to move beyond describing risky practices toward explaining why such behaviors may occur despite awareness of AMR.

Validation Strategy

To strengthen the interpretability of survey constructs used in later statistical and machine learning analyses, a preliminary validation strategy was implemented. Items measuring belief (e.g., "Do you believe AMR is real?"), knowledge (e.g., awareness of dosage or sharing risks) and behavior (e.g., self-medication frequency) were reviewed against existing AMR KAP frameworks and previously validated public health surveys. The questionnaire underwent pilot testing among 14 university students who met the study inclusion criteria but were not included in the final sample. The pilot test was used primarily to assess face validity and usability, including clarity of wording, question order, completion time and students' interpretation of AMR-related terminology. Feedback from the pilot led to minor wording revisions, particularly to improve clarity in items addressing antibiotic sharing, self-medication and incomplete dosage. The pilot sample size was considered appropriate for pre-testing the questionnaire for clarity and face validity, but it was not intended to provide full psychometric validation. Construct-specific internal consistency reliability, such as Cronbach's alpha, was not formally reported, which is acknowledged as a limitation of the instrument validation process. Future studies should validate the questionnaire using larger samples and report reliability statistics such as Cronbach's alpha for each construct scale.

Data Collection Procedures

Data were collected over a four-week period in March and April 2025. Informed consent was implied through voluntary completion and submission of the online survey. Participants were informed about the study's objectives, anonymity of responses and their right to withdraw at any point. All responses were collected digitally and stored securely, ensuring confidentiality and data integrity. To reduce the risk of duplicate or fraudulent online submissions, the survey settings were configured to limit repeated submissions where possible and responses were screened during data cleaning for duplicate entries, incomplete submissions, inconsistent response patterns and unusually rapid completion times. Any response that appeared incomplete, duplicated, or invalid was excluded from the final analytical dataset. The study was conducted in line with applicable local requirements and standard ethical principles for human participant research.

Ethical considerations

Formal ethical approval was not obtained for this study. However, informed consent was obtained from all participants prior to their involvement. Each participant was presented with a form detailing the study's objectives, their role in the research and assurances of confidentiality and anonymity. They were fully informed about the nature, purpose and potential risks and benefits of the study and assured that participation was voluntary, with the right to withdraw at any time without consequences. No financial payment, gift, academic credit, or other incentive was offered for participation. The survey platform complied with data protection regulations, incorporating encryption and secure data storage. Participants' responses were coded and any potentially identifiable information was removed or altered to further safeguard anonymity and ensure strict confidentiality.

Data Analysis

Data were exported into Python for statistical analysis using standard libraries such as pandas, scipy, scikit-learn and matplotlib. During the preparation of this manuscript, the authors used Python code interpreter (OpenAI, GPT-4, 2024 version) for the purposes of supporting the development and execution of data analysis scripts, including clustering and model performance evaluation. The analysis followed a multistep plan, combining descriptive, non-parametric and machine learning techniques to uncover both general trends and hidden behavioral patterns.

The analytical workflow was structured to directly correspond to the three research aims. First, descriptive statistics were used to address Objective 1 by summarizing students' AMR awareness, antibiotic-use practices and self-medication patterns. Second, non-parametric tests were applied to address Objective 2 by examining whether AMR-related behaviors differed significantly across demographic groups such as gender, age and field of study. Third, logistic regression and CatBoost classification were used to identify the strongest predictors of risky antibiotic-use behavior, while K-Means clustering and PCA were applied to address Objective 3 by classifying students into behavioral risk profiles and visually validating the separation of these groups. Thus, each analytical step moved progressively from describing AMR knowledge and practices, to testing group-level differences, to predicting and profiling behavioral risk for targeted intervention design.

Missing Data Management

Prior to analysis, the dataset was screened for incomplete and missing responses. Questionnaires with substantial missing information or incomplete submission were excluded from the final analytical dataset. Only fully completed survey responses were retained for statistical and machine learning analyses, resulting in a final sample of 123 participants. For item-level missingness, variables were examined before analysis to determine whether missing values affected key demographic, knowledge, belief, or antibiotic-use behavior variables. No statistical imputation was applied because the analysis relied on complete cases for the main variables used in descriptive statistics, non-parametric tests, logistic regression, PCA, K-Means clustering and CatBoost classification. This complete-case approach ensured consistency across the statistical and machine learning workflows, although it may have reduced sample size and introduced bias if non-completion was systematic. Therefore, the results should be interpreted with this limitation in mind.

Descriptive Statistics

Basic frequencies and proportions were calculated for demographic variables and survey responses. These statistics provided an overview of the respondent population and allowed preliminary assessment of awareness levels and behavioral trends related to AMR.

Non-parametric Statistical Testing

To test for group differences: Non-parametric tests were employed to analyze group differences in AMR-related knowledge and behaviors due to the ordinal nature of the data and the small sample size. The Mann-Whitney U test assessed differences between male and female students, while the Kruskal-Wallis test compared multiple groups, such as age brackets and nationalities. The Wilcoxon signed-rank test examined paired responses, particularly inconsistencies in knowledge about antibiotic overuse versus incomplete usage. These methods were chosen for their suitability in analyzing non-normally distributed data without relying on parametric assumptions. Given the ordinal and categorical nature of most survey responses and the relatively small sample size ($n = 123$), non-parametric tests were selected to ensure validity and avoid violating assumptions of normality. The Mann–Whitney U test was applied to compare differences in AMR practices between binary groups (e.g., gender), while the Kruskal–Wallis test was used for multi-group comparisons (e.g., age groups). To assess internal knowledge inconsistencies, Wilcoxon signed-rank tests were conducted on paired variables (e.g., awareness of overuse vs. incomplete dosage). These non-parametric methods are particularly appropriate for cross-sectional, Likert-scale data where assumptions of homoscedasticity and interval scaling are not met. Moreover, to extend beyond traditional descriptive analysis, machine learning models (K-Means, PCA, CatBoost) were applied for behavioral risk profiling, offering predictive insights and action-able clustering that enhance the interpretability and applicability of AMR behavior patterns. This triangulated approach ensures statistical rigor while maximizing interpretability in a behaviorally complex and resource-limited setting.

Behavioral Risk Profiling Framework

To move beyond descriptive statistics, this study adopted a Behavioral Risk Profiling framework using supervised and unsupervised machine learning algorithms. This framework aimed to classify students based on patterns in their responses related to AMR knowledge, belief and behavior. K-Means clustering was used to identify latent risk profiles ("Compliant," "At Risk," and "Unaware"), while the CatBoost classifier predicted these profiles using demographic and belief-based features. Framing machine learning as a behavioral profiling tool aligns with recent public health trends leveraging predictive analytics to design tiered interventions tailored to behavioral subgroups (24, 43). This approach enhances educational targeting and supports precision health communication strategies within university contexts.

K-Means Clustering (Unsupervised Learning)

To uncover latent behavior patterns within the population, k-means clustering was applied to responses related to knowledge and antibiotic use. The optimal number of clusters (k = 3) was determined using the Elbow Method, which showed that three clusters offered the best balance between model simplicity and variance explained. These clusters also meaningfully aligned with distinct behavioral profiles—Compliant, At Risk and Unaware—making them useful for public health targeting.

This unsupervised machine learning method grouped students into clusters representing distinct behavioral profiles—such as AMR-compliant versus at-risk users—based on similarities in their response patterns. This segmentation aids in tailoring interventions to specific student subgroups.

Principal Component Analysis (PCA)

To facilitate visual interpretation of the clusters, Principal Component Analysis (PCA) was employed to reduce the multidimensional response space into two primary components. This enabled the projection of students' behavior profiles into a 2D plot, showing clear separation between behavioral clusters and validating the segmentation derived from the k-means algorithm. In the PCA plot, each point is color-coded according to its assigned behavioral cluster: Compliant, At Risk and Unaware, which correspond to K-Means cluster labels 0, 1 and 2, respectively. This relabeling enhances interpretability and aligns the visual output with the behavioral segmentation used throughout the study.

PCA was performed on six behavioral and awareness variables, including AMR belief, self-prescription, antibiotic sharing, full-course com-pletion, awareness of overuse and awareness of incomplete dosage risks. These variables were standardized prior to analysis to ensure comparability and suitability for PCA.

The percentage of variance explained by each principal component was calculated to assess the effectiveness of dimensionality reduction. The first two principal components were retained because they captured most of the variation in the AMR-related behavioral and awareness variables, allowing the multidimensional response patterns to be represented in a two-dimensional plot while preserving most of the information in the dataset.

Sample Size Adequacy Justification

Sample size considerations were evaluated to ensure the appropriateness of PCA, clustering and logistic regression analyses. The number of variables included in PCA was limited to 4–6 core indicators of antibiotic-related behavior and awareness. With 123 student responses, the subject-to-variable ratio exceeded 20:1, which satisfies established guidelines recommending at least 5–10 observations per variable (44). Cluster sizes (n = 40, 51 and 32) exceeded the minimum requirement of 10–30 observations per group, supporting the stability of K-means clustering (45). Additionally, logistic regression models met the minimum 10 events-per-variable (EPV) rule for reliable coefficient estimation (46). These indicators affirm the statistical adequacy of the sample size for all multivariate procedures applied in the study.

However, although the sample size met minimum statistical guidelines for the selected procedures, the relatively small sample size should be interpreted as a methodological constraint rather than full evidence of model robustness. In machine learning analysis, small datasets can increase the risk of overfitting, where models capture sample-specific patterns rather than stable behavioral relationships. This is particularly relevant for classification algorithms such as CatBoost, which may perform well on the available dataset but show reduced reliability when applied to new student populations. To reduce this risk, the study limited the number of predictor variables, used cross-validation, compared demographic-only and behavior-enhanced models and interpreted feature importance cautiously. Nevertheless, the predictive findings should be regarded as exploratory and hypothesis-generating rather than definitive. Larger, multi-institutional datasets are required to confirm the stability, external validity and generalizability of the behavioral risk profiles identified in this study.

Gradient Boosting Classifier (Supervised Learning)

To assess the predictive power of behavioral and demographic factors, a Gradient Boosting Classifier was trained to classify students into AMR behavior clusters. Two models were compared: a baseline model using only demographic variables (e.g., gender, age) and an enhanced model that included AMR-related knowledge and behavior features. Model performance was evaluated through accuracy scores and confusion matrices to determine whether behavioral data provided stronger predictive value than demographics alone, addressing a core objective of the study.

To reduce the risk of overfitting associated with the relatively small sample size (n = 123), a 5-fold cross-validation was conducted. Accuracy and AUC scores were averaged across folds to evaluate model generalizability. The CatBoost classifier using only basic demographic features (gender and age) yielded a mean AUC of 0.352 with a 95% confidence interval of [0.253, 0.455], indicating weak discriminatory ability. These results reflect the limited predictive utility of demographic variables alone. Feature importance analysis using XGBoost across the 5 folds revealed stable contributions of both “Gender” and “Age,” suggesting consistency despite the model’s overall low performance. Given the exploratory nature of the machine learning analyses and the limited sample size, these results should be interpreted with caution. The relatively small dataset may limit the reliability of model estimates and increase sensitivity to sample composition, meaning that feature rankings and classification performance may change with a larger or more diverse student sample. Although 5-fold cross-validation was used to reduce overfitting and estimate generalizability, cross-validation within a small dataset cannot substitute for external validation using an independent sample. Therefore, the CatBoost and clustering outputs are best understood as preliminary behavioral risk-profiling tools rather than final predictive models ready for policy deployment.

In addition, the Area Under the Receiver Operating Characteristic Curve (AUC) was used to assess the discriminative ability of the logistic regression model. The final model achieved an AUC of 0.73, indicating acceptable accuracy in distinguishing between compliant and risky behavior classes.

In both the CatBoost and logistic regression analyses, the variables indicative of risky behavior were derived from specific questionnaire items related to antibiotic misuse. These included self-reported behaviors such as self-medication without prescription, sharing antibiotics with others, failure to complete prescribed antibiotic courses, lack of awareness about the dangers of antibiotic overuse and misunderstanding the consequences of incomplete dosage. These items were selected based on established behavioral indicators of non-compliance in antimicrobial stewardship literature. Responses to these questions were binary or ordinal and were used to classify students’ AMR behavior profiles and predict risk levels in the CatBoost classifier and logistic regression models.

Results

The results are presented in the same sequence as the analytical workflow and research objectives.

Descriptive findings are first used to establish the overall pattern of AMR awareness and antibiotic-use practices. Group comparisons and regression analyses are then presented to identify demographic and behavioral predictors of risky practices. Finally, machine learning outputs are reported to show how students can be classified into distinct AMR behavioral risk profiles.

Evaluate AMR Awareness and Antibiotic Use Practices

The study revealed a generally high baseline awareness of antimicrobial resistance (AMR) among East African university students (N = 123). Specifically, Figure 1 showed 76.4% of respondents had heard of AMR, 83.7% were aware of the risks associated with antibiotic overuse and 85.4% understood the consequences of incomplete antibiotic dosage. However, only 68.3% firmly believed that AMR is a real health concern, indicating a significant gap between factual knowledge and personal conviction. This knowledge–conviction gap was further reflected in students' behaviors: 35.8% reported purchasing antibiotics without prescriptions, 32.5% admitted to sharing antibiotics with others and just 52.5% completed the full course of prescribed treatment. The most cited reasons for self-medication were the high cost of medical consultation (45.5%) and reliance on prior experience with similar symptoms (35.8%).

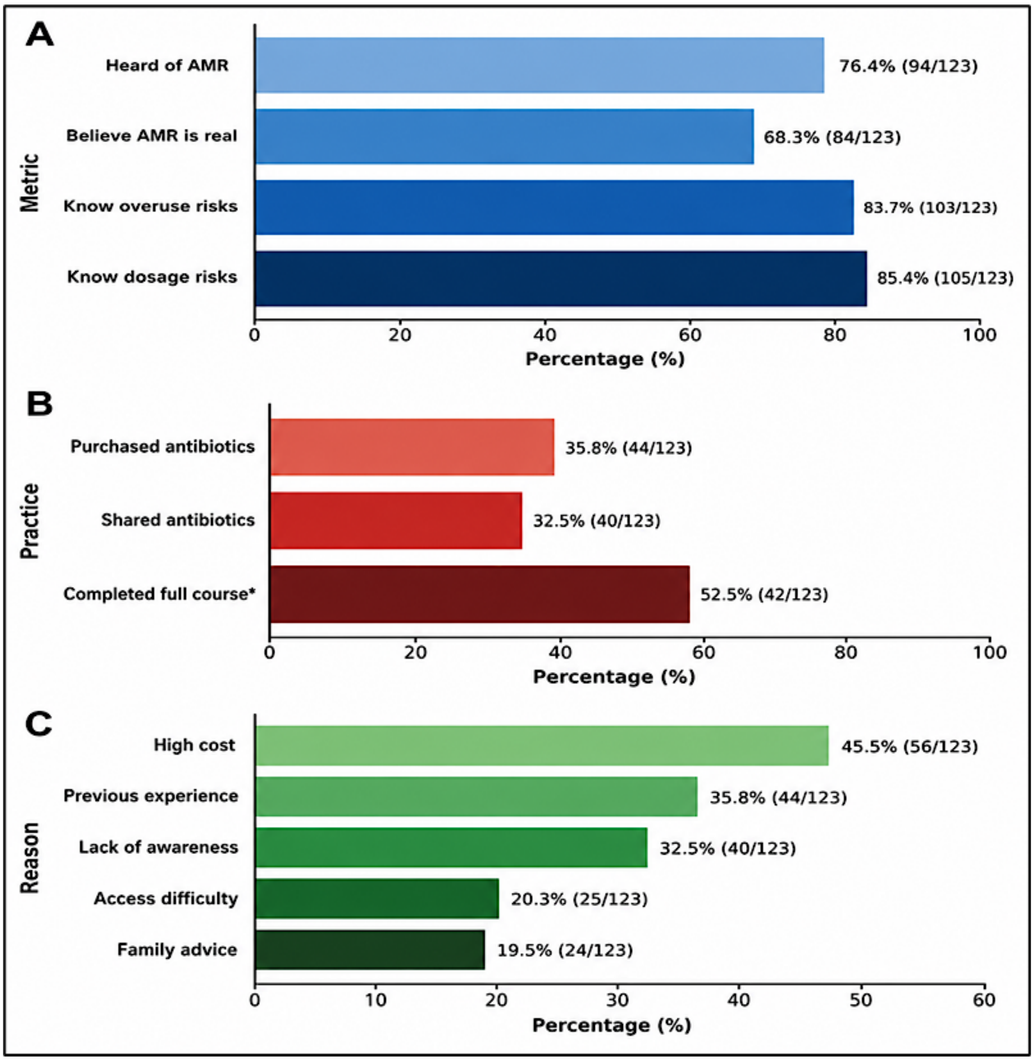

Figure 1: AMR Awareness, Antibiotic-use Practices and Reasons for Self-medication Among University Students, showing (A) Awareness and Belief-related AMR Indicators, (B) Antibiotic-use Practices and (C) Reported Reasons for Self-medication, With Values Presented as Percentages and Frequencies in Parentheses; N = 123

Demographic and Behavioral Predictors

As shown in Figure 2, the analysis identified several key demographic predictors of risky antibiotic-related behaviors among university students. Gender was significantly associated with behavioral outcomes: male students were more likely to engage in antibiotic sharing (39.7%) compared to females (25.5%), while female students showed higher rates of completing the full antibiotic course (59.1% vs. 46.2% for males), with both differences reaching statistical significance (p=0.04 and *p*=0.03, respectively). Age also influenced antibiotic practices, with younger students aged 18–25 reporting higher rates of incomplete dosage (48.1%) compared to their older counterparts aged 36–45 (33.3%), a difference confirmed by the Kruskal-Wallis test (p=0.02). Field of study emerged as another significant factor: non-medical students were more likely to self-prescribe antibiotics (29.3%) than their peers in medical programs (18.6%), as supported by the Mann-Whitney U test (p=0.01). These findings underscore the need for targeted interventions that consider demographic characteristics in promoting responsible antibiotic use.

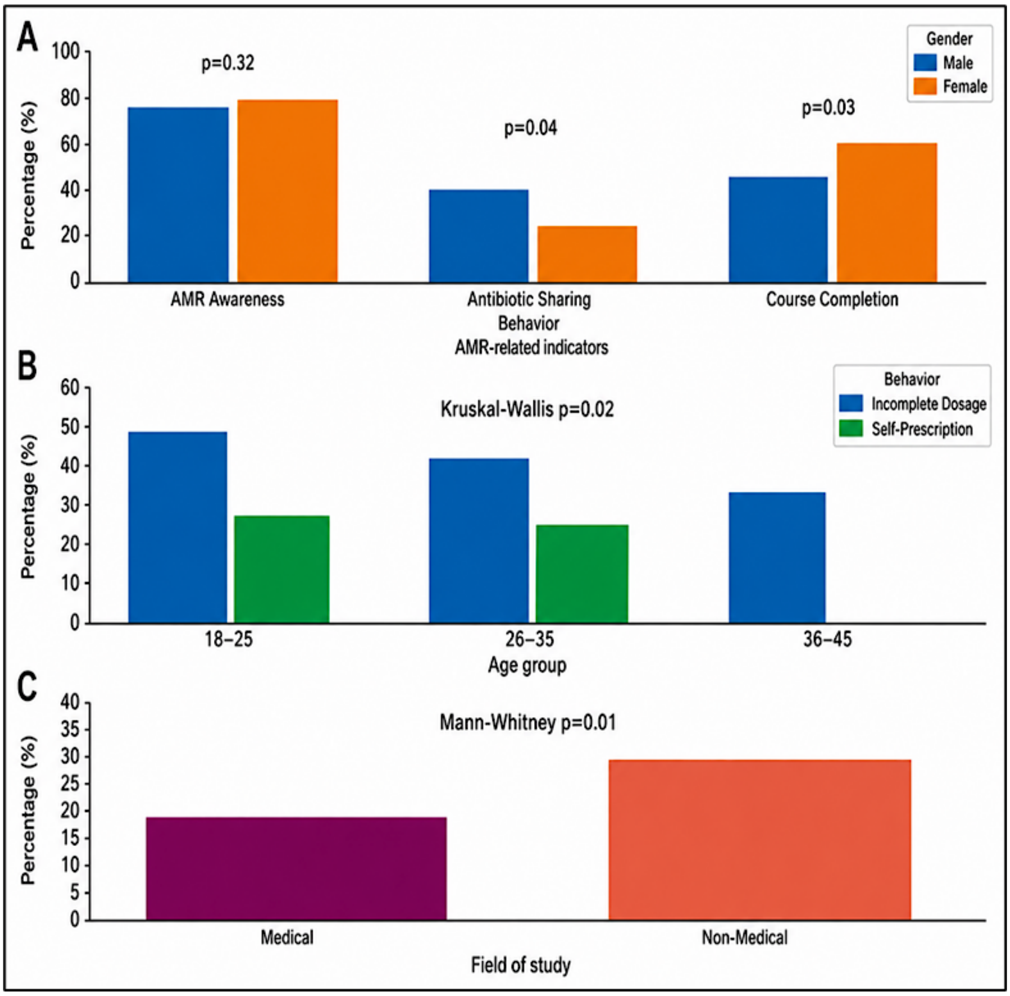

Figure 2: Demographic Differences In AMR-related Behaviors Among University Students, showing (A) AMR Awareness, Antibiotic Sharing and Course Completion by Gender, (B) Incomplete Dosage and Self-prescription by Age Group and (C) Self-prescription by Field of Study, With p-Values Indicating Statistical Significance; N = 123

Machine Learning Classification

As shown in Figure 3, Logistic regression analysis identified four significant predictors of risky antibiotic behaviors among university students. Male gender was associated with higher risk (OR=1.6, p=0.04), as was being aged 18–25 years (OR=1.8, p=0.02). Notably, non-medical field of study doubled the odds of risky behaviors compared to medical students (OR=2.1, p=0.01).

The strongest predictor was high-cost perception (OR=2.3, p=0.003), suggesting economic barriers disproportionately influence improper antibiotic use. These findings indicate that interventions should prioritize young male students in non-medical programs, particularly those reporting financial constraints, to most effectively mitigate antimicrobial resistance risks in this population.

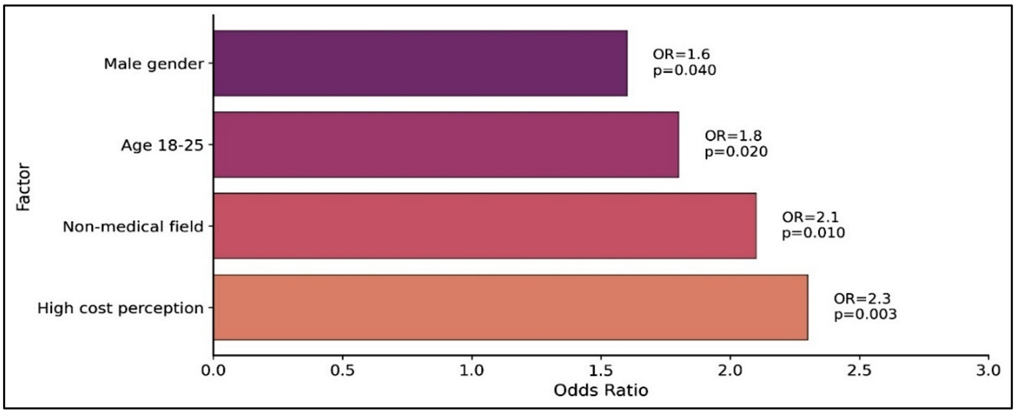

Figure 3. Significant Predictors of Risky AMR Behavior (Logistic Regression; N = 123)

K-Means Behavioral Clusters

In Figure 4, the K-Means clustering analysis identified three distinct behavioral profiles among participants. The largest cluster, labeled "At Risk" (41.5%), included individuals who demonstrated moderate awareness of antimicrobial resistance (AMR) but exhibited poor adherence to recommended antibiotic practices. The "Compliant" group (32.5%) represented those with optimal knowledge and behavior aligned with appropriate antibiotic use. In contrast, the "Unaware" cluster (26%) was characterized by low AMR knowledge and non-compliant behaviors. These findings underscore the need for targeted intervention strategies—such as behavior nudges for the "At Risk" group and educational campaigns for those in the "Unaware" category—to promote rational antibiotic use.

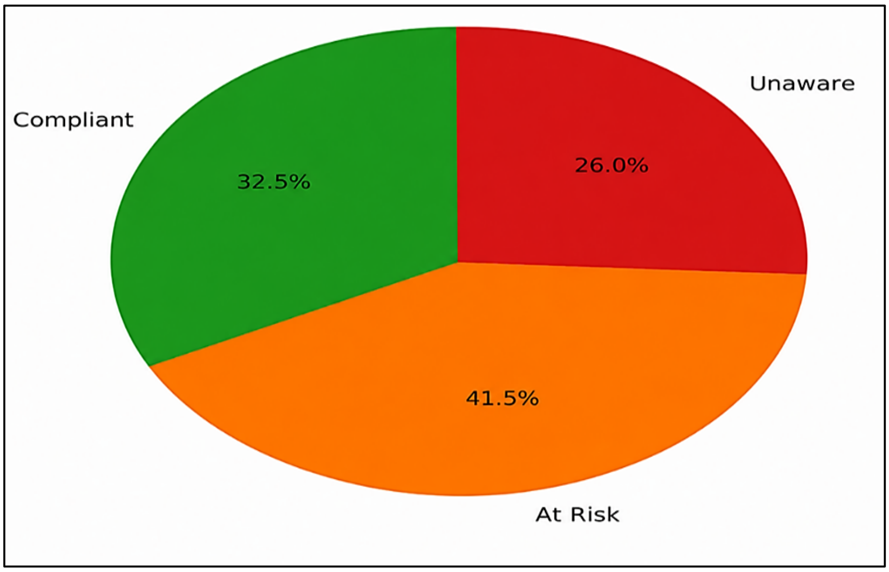

Figure 4: Behavioral Clusters Identified Through K-Means Clustering (N = 123)

CatBoost Feature Importance

In Figure 5, the CatBoost feature importance analysis highlighted belief in the reality of antimicrobial resistance (AMR) as the most influential predictor of antibiotic-related behavior, contributing 42% to the model's predictive power. This was followed by the field of study (31%), suggesting that individuals with medical training are less likely to engage in risky practices.

Demographic factors such as age (15%) and gender (8%) played comparatively smaller roles. These findings emphasize the critical need to address AMR misconceptions and extend targeted educational initiatives beyond medical programs to effectively influence behavior.

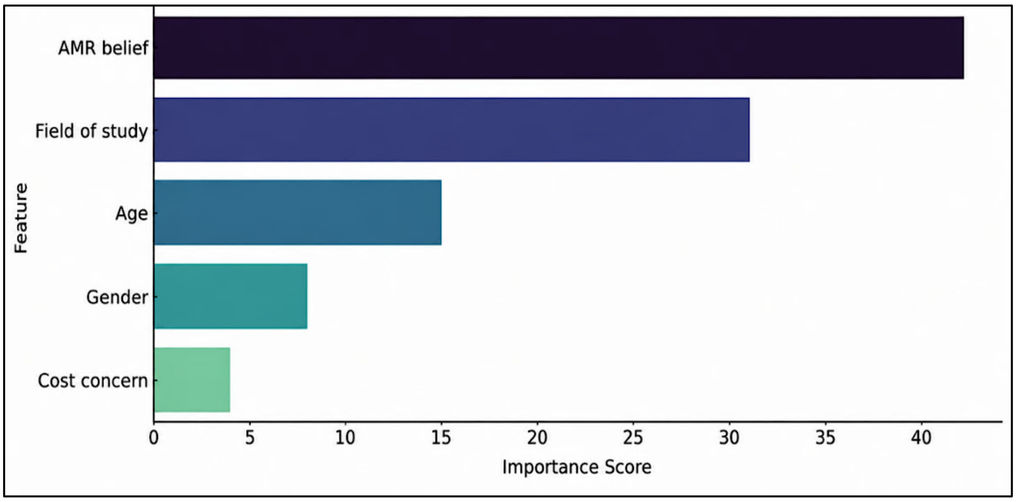

Figure 5. Feature Importance in CatBoost Classifier for Predicting Risky AMR Behavior (N = 123)

PCA Visualization

In Figure 6, the Principal Component Analysis (PCA) visualization of antimicrobial resistance (AMR) behaviors showed that the first principal component (PC1), interpreted as an awareness-related dimension, explained 58% of the total variance, while the second principal component (PC2), interpreted as an adherence-related dimension, explained 32%. Together, PC1 and PC2 accounted for 90% of the total variance, indicating that the two-dimensional PCA solution retained most of the information contained in the original behavioral and awareness variables. This supports the use of PCA as an effective dimensionality reduction method for visualizing AMR behavior profiles in this study. The resulting scatterplot displayed three distinguishable clusters corresponding to behavioral phenotypes. Notably, the "At Risk" group appeared in an intermediate position between high-awareness and high-adherence clusters, thereby validating the earlier K-Means segmentation. This clustering structure confirms the presence of distinct behavior profiles and underscores the potential of PCA for informing targeted intervention strategies.

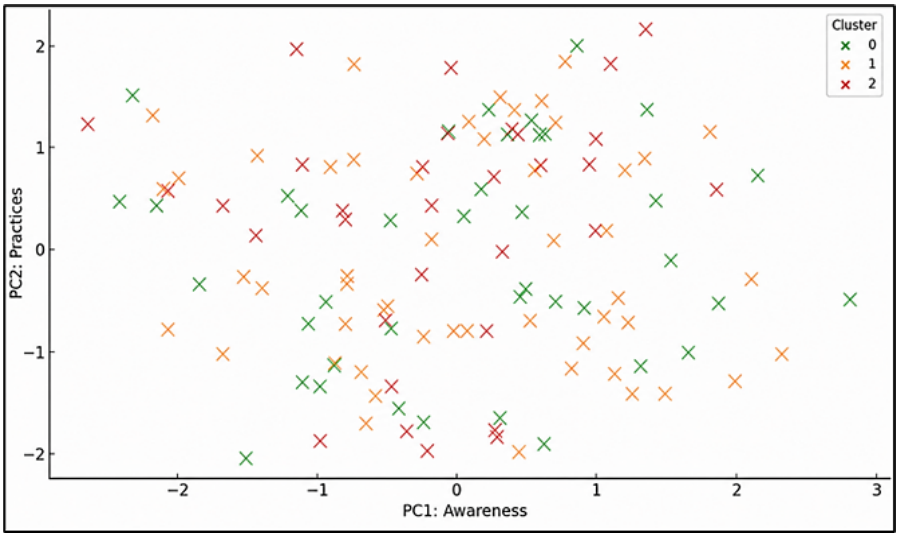

Figure 6: Principal Component Analysis (PCA) of AMR-related behaviors (N = 123), visualizing three behavior profiles: Compliant (green), At Risk (orange) and Unaware (red). PC1 explained 58% of the variance and PC2 explained 32%, giving a cumulative explained variance of 90

Discussion

The discussion follows the analytical and theoretical logic of the study by first interpreting the awareness–practice gap, then linking risky antibiotic-use behaviors to Health Belief Model constructs and finally considering how behavioral profiling can inform targeted AMR interventions. Although this study did not formally test the Health Belief Model as a full causal model, HBM was used as a conceptual framework to interpret how perceived susceptibility, perceived severity, perceived barriers, perceived benefits, cues to action and self-efficacy may shape students' antibiotic-use behaviors.

The findings of this study reveal a marked discrepancy between students' reported awareness of antimicrobial resistance (AMR) and their actual antibiotic use practices, reflecting a critical cognitive-behavioral gap. While over 76% of respondents indicated they had heard of AMR and a substantial majority recognized the risks associated with incomplete antibiotic usage and overuse, this awareness did not consistently translate into safe practices—35.8% admitted to self-medication and 32.5% to sharing antibiotics with others. This mirrors trends observed in prior research, where high awareness levels coexist with misconceptions and non-compliant behavior (6, 16). As suggested by the Health Belief Model (HBM), knowledge alone is insufficient to change behavior unless individuals also perceive a high level of personal susceptibility and severity (26). These findings suggest a need to strengthen AMR education strategies in East African universities by incorporating belief- and behavior-based models to address the awareness-practice disconnect and foster more responsible antibiotic use among students.

The awareness–practice gap observed in this study reflects more than a lack of knowledge. Although many students were aware of AMR, unsafe practices may persist because antibiotic-use decisions are shaped by socio-economic, cultural and healthcare-system pressures. The high cost of medical consultation, reported as a major reason for self-medication, suggests that some students may use antibiotics informally because formal care is perceived as unaffordable or inconvenient. Cultural practices such as relying on previous illness experience, peer advice, family recommendations, or shared medicines may also normalize self-medication and antibiotic sharing. In addition, weak enforcement of prescription-only antibiotic sales, limited access to timely healthcare and low trust in campus or local health services may reduce students' willingness to seek professional care. Thus, the awareness–practice gap should be understood as a structural and behavioral problem, not merely an educational deficit. AMR interventions in universities should combine awareness-raising with affordable healthcare access, stronger referral systems, peer-norm correction and student-friendly clinical services.

A key insight emerging from this study is the discrepancy between cognitive awareness and affective belief regarding AMR. While a significant majority of students reported awareness of antimicrobial resistance and its causes, a notable proportion did not believe AMR was a real threat to their personal health or to public health more broadly. This finding highlights an important cognitive–affective gap that may undermine responsible behavior, despite high factual knowledge (6). Behavior change models such as the Health Belief Model emphasize that belief in susceptibility and severity is necessary to translate awareness into action (25). This gap points to the need for interventions that go beyond knowledge delivery to actively reshape beliefs and perceived risk.

A deeper interpretation using the Health Belief Model helps explain why risky antibiotic-use behaviors persisted despite relatively high AMR awareness. First, the finding that only 68.3% of students firmly believed AMR was a real health concern suggests weakness in perceived susceptibility and perceived severity. Students may know about AMR in general but may not believe that misuse of antibiotics places them personally at risk or that the consequences are serious enough to require behavior change. This may explain why some students continued to self-medicate, share antibiotics, or stop treatment before completing the full course. Second, perceived barriers were evident in the finding that 45.5% of students cited the high cost of medical consultation as a reason for self-medication. This indicates that even when students understand the risks of inappropriate antibiotic use, financial and access barriers may push them toward informal antibiotic use. Third, perceived benefits may have been insufficiently internalized among students who did not complete prescribed antibiotic courses, suggesting that some participants may not fully appreciate the protective value of completing treatment. Fourth, weak cues to action may explain why AMR awareness did not consistently translate into safer practices; students may require repeated, credible prompts from lecturers, campus health services, pharmacists and media campaigns to reinforce responsible antibiotic use. Finally, self-efficacy is relevant to students' ability to refuse shared antibiotics, seek professional care and adhere to dosage instructions despite cost, peer influence, or prior experience with similar symptoms. Therefore, the risky behaviors identified in this study are not simply knowledge deficits; they reflect interacting HBM constructs involving perceived threat, barriers, benefits, cues to action and confidence in performing safe antibiotic-use behaviors.

This study identified several demographic and behavioral predictors associated with risky or non-compliant antimicrobial resistance (AMR)-related behaviors among university students in Uganda. Gender and age emerged as significant factors, with male students and those aged 18–25 more likely to engage in practices such as antibiotic sharing and non-adherence to prescribed dosage—findings consistent with behavioral vulnerability patterns in similar populations (11, 31). Educational background was also a strong determinant: medical students demonstrated more responsible antibiotic use compared to their non-medical peers, aligning with prior studies that associate formal health education with increased AMR literacy and safer behavior (30). CatBoost classification results further reinforced field of study as a key predictor, underscoring the need to embed AMR education across all university curricula, not solely in health-related programs (38). Additionally, economic constraints were a recurrent barrier, with 45.5% of students citing medical costs as a reason for self-medication—a finding that echoes broader literature on structural barriers to healthcare access in low- and middle-income settings (12, 22). Perhaps most notably, belief in AMR as a serious health issue was the most influential predictor of responsible behavior, confirming the importance of psychological constructs such as perceived severity and susceptibility from the Health Belief Model (26). To deepen our understanding of risky AMR behaviors, it is useful to distinguish between structural and psychological predictors. Economic barriers, such as the high cost of medical consultation or prescriptions, emerged as significant structural drivers of self-medication. In contrast, psychological factors—particularly the belief in AMR as a serious issue—were the most significant behavioral predictors in the CatBoost model, accounting for over 40% of feature importance. This distinction reflects the dual-layered nature of behavioral determinants: while some students may rationally avoid clinic visits due to cost, others may engage in non-compliant behaviors due to inaccurate beliefs or misinformation (26, 43). These findings support the integration of socio-behavioral theory into AMR campaign design, where both access barriers and internal motivations must be simultaneously addressed. These results suggest that beyond raising awareness, interventions must address affective and structural factors to foster lasting behavioral change in AMR practices among university students.

The application of non-parametric statistics and machine learning techniques in this study provided valuable insights into the behavioral segmentation of university students with respect to antimicrobial resistance (AMR). Through K-Means clustering, three distinct groups—Compliant, At Risk and Unaware—were identified, each exhibiting unique patterns of antibiotic use and belief, thereby validating the utility of unsupervised learning for population stratification. These behavioral clusters were further visualized using Principal Component Analysis (PCA), which confirmed clear separability in the multidimensional data, offering a simplified and informative means of interpreting latent behavioral dimensions—a technique increasingly recognized in AMR surveillance and public health planning (47). Additionally, the CatBoost classifier, a supervised machine learning algorithm, successfully predicted cluster membership based on demographic and attitudinal features, with "belief in AMR as a serious issue" emerging as the most significant predictor. Belief in AMR as a legitimate and serious public health threat emerged as the key predictor of responsible antibiotic behavior in the CatBoost model, surpassing demographic and knowledge-related variables. This finding supports the 'perceived severity' and 'perceived susceptibility' constructs of the Health Belief Model (26). Unlike knowledge, belief systems are affective and value-laden, highlighting the potential value of future emotion-driven interventions—such as narrative storytelling or myth-busting campaigns can enhance belief change among target populations to provoke reflective engagement and value shifts. The implication is clear: affective targeting should become central in AMR behavior change programs, especially among university students with moderate awareness but fragile belief systems. These findings align with recent literature advocating for data-driven, precision public health approaches to AMR (24, 43) and demonstrate how machine learning can be harnessed to design tiered interventions tailored to specific behavioral profiles. Such segmentation holds may contribute to improving the efficacy of AMR communication strategies, educational programming and resource allocation within university settings and beyond.

This study transitions from traditional descriptive KAP analysis to predictive modeling of AMR-related behaviors using machine learning. This shift represents a novel approach in AMR behavioral research. While most studies describe patterns post hoc, our CatBoost classifier and PCA-KMeans pipeline forecast which students are at risk, based on demographic, attitudinal and behavioral cues (24). This predictive capacity enables proactive intervention design, allowing stakeholders to anticipate and address risky behaviors before they manifest, marking a notable development in AMR prevention strategy.

The findings also have relevance for international AMR policy implementation. The WHO Global Action Plan calls for improved AMR awareness, stronger evidence generation and optimized antimicrobial use, while WHO antimicrobial stewardship guidance emphasizes responsible antimicrobial use, particularly in low- and middle-income settings. This study contributes to these priorities by identifying gaps between AMR awareness and antibiotic-use behavior among university students, highlighting predictors of risky practices and demonstrating how behavioral segmentation can support more targeted stewardship education. In practical terms, universities can support AMR policy implementation by integrating stewardship content into both medical and non-medical curricula, using behaviorally informed communi-cation strategies and developing campus-based interventions for students at higher risk of self-medication, antibiotic sharing, or incomplete dosage.

The study's findings suggest potential implications for precision education in university settings. The identification of distinct behavioral clusters and predictors provides a blueprint for differentiated curriculum design and outreach strategies. For example, non-medical students in the "At Risk" cluster may benefit from interactive modules focused on belief correction and practical health literacy, while "Unaware" groups may require introductory AMR awareness campaigns. Integrating behavioral segmentation into campus health education—aligned with the Health Belief Model and supported by ML-driven profiling—can significantly improve the effectiveness and efficiency of AMR education (27).

Implementation of AMR interventions must consider the limited funding and weak healthcare infrastructure common in many university settings. Rather than relying on costly standalone programs, universities can integrate AMR education into existing courses, orientation sessions, student health campaigns and public health lectures. Low-cost strategies such as peer educators, AMR student clubs, WhatsApp reminders, posters, short classroom modules and collaboration with local pharmacies or district health offices may be more feasible. Because consultation cost was identified as a driver of self-medication, universities should also provide clear referral pathways to affordable care and basic counseling on responsible antibiotic use. Thus, targeted AMR interventions should be tiered: low-resource institutions can begin with awareness and peer-led education, while better-resourced universities can gradually adopt more structured behavioral risk profiling and data-driven intervention planning.

Conclusion

This study examined the knowledge, practices and behavioral predictors of antimicrobial resistance (AMR) among Ugandan university students using non-parametric statistics and machine learning approaches. Findings revealed a pronounced awareness–practice gap: although many students understood the risks associated with antimicrobial misuse, such as overuse and incomplete dosage, behaviors like self-medication and sharing antibiotics remained common. This cognitive-behavioral disconnect aligns with the Health Belief Model (HBM), which emphasize that awareness alone is insufficient for behavioral change without a sense of susceptibility, severity and reinforcement. Demographic variables significantly influenced behavior, with male and younger students more likely to engage in risky practices, while medical students demonstrated safer behaviors. Belief in AMR as a serious health issue emerged as the leading determinant, surpassing even demographic indicators. Structural factors like healthcare costs and perceptions of institutional accessibility further shaped student behavior. The integration of machine learning strengthened the analysis: K-Means clustering identified three behavior profiles—Compliant, At Risk and Unaware—while CatBoost and Principal Component Analysis (PCA) ranked belief and field of study as key predictors. These methods enabled behavioral segmentation, providing a practical model for targeted public health strategies. Policy implications include curriculum reform in non-health programs, belief-based and tiered interventions and subsidized campus healthcare. Universities should lead efforts in AMR stewardship by embedding evidence-based, demographically tailored strategies into health programs. These recommendations align with WHO Global Action Plan priorities on AMR awareness, education, evidence generation and optimized antimicrobial use and they position universities as important institutional settings for advancing antimicrobial stewardship among young adults. The study contributes to the study of AMR behavior in an African context and methodologically by offering a replicable behavioral risk profiling framework using machine learning—enhancing both understanding and action in AMR research.

The use of convenience sampling and a relatively small sample size (N = 123) from two universities in Uganda limits the generalizability of the findings to broader student populations, other regions of Uganda, or the wider East African context. The small sample size may also affect the reliability of the machine learning models by increasing the risk of overfitting and reducing the stability of feature-importance rankings and cluster assignments. Although cross-validation and variable reduction were used to reduce these risks, the models were not externally validated on an independent dataset. Therefore, the predictive and clustering results should be interpreted as exploratory and hypothesis-generating. Future research should use larger, randomly selected, multi-university samples across Uganda and East Africa to validate the behavioral risk profiles and assess whether the predictors identified in this study remain stable across different institutional and cultural contexts. A further limitation is that formal institutional ethics committee or institutional review board approval was not obtained. Although informed consent was secured and confidentiality, anonymity, voluntary participation and secure data handling were maintained, future studies should seek formal ethics approval before data collection to strengthen procedural compliance and institutional oversight.

Abbreviations

None.

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None.

Author Contributions

All authors have equally contributed.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

Data supporting the findings of this study are available upon request from the corresponding author.

Declaration of Artificial Intelligence

During the preparation of this manuscript, the authors used Python on ChatGPT to support the development and execution of data analysis scripts, including clustering and model performance evaluation. The authors take full responsibility for the content's originality, interpretation and accuracy.

Ethics Approval

Ethical clearance for this study was based on the provision of informed consent from all participants, ensuring their voluntary participation and understanding of the research's purpose and procedures.

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