Integrating AI-Driven Triage into Digital Pharmacy Systems for Rational Antibiotic Use in Low-Resource Settings

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Abstract

Antimicrobial resistance (AMR) is becoming a bigger threat to global health, especially in low- and middle-income countries (LMICs), where antibiotics are often given out without a prescription. This study presents a hybrid Artificial Intelligence (AI) framework to improve rational antibiotic utilization by integrating pharmacies, telemedicine practitioners, and policymakers through an integrated digital infrastructure. The digital intervention system was implemented in 28 community pharmacies and showed significant improvements in how people used antibiotics. Specifically, the percentage of people who self-medicated with antibiotics dropped from 4.05% to 0.86%, and the percentage of people who bought antibiotics with a prescription jumped from 27.6% to 43.5%. We propose an AI framework that combines a machine learning (ML)-based and a large language model (LLM)-based symptom checker for intelligent triage and clinical decision support. These models will enable efficient analysis of both structured and narrative symptom data, which will help pharmacists provide advice and doctors refer patients right away. The suggested model demonstrates a scalable, data-driven, and human-in-the-loop approach to antibiotic stewardship, with the potential to support future AMR mitigation and healthcare accessibility in LMICs settings.

Introduction

Antimicrobial resistance (AMR) has become one of the most critical global health issues of the twenty-first century. The World Health Organization (WHO) includes AMR on its list of the top ten public health threats. In 2019, resistant bacterial infections caused almost 4.95 million deaths around the world (Murray et al. 2022). By 2050, deaths caused by AMR are expected to exceed 10 million each year (de Kraker, Stewardson, and Harbarth 2016). This will cost the healthcare system an extra trillion dollars and cause significant economic problems, especially in countries with few resources (Organization 2023). The rise of AMR not only makes life-saving drugs less effective, but it also sets back years of progress in treating infectious diseases, performing safe surgeries, and keeping mothers and babies healthy.

The crisis is especially acute in low- and middle-income countries (LMICs), where healthcare systems struggle with issues such as inadequate diagnostic facilities, a shortage of qualified physicians, and weak regulation of drug sales (Okeke et al. 2005; Kunin 1993; Chokshi et al. 2019). Community pharmacies are the primary source of medical treatment in many LMICs. Due to patient demand and the lack of clinical options, these pharmacies usually offer antibiotics without a prescription. As a result, many people self-medicate and don't complete their antibiotic courses, which can lead to bacterial resistance (Chokshi et al. 2019). Large-scale programmes that facilitate access to trustworthy health information and promote prudent medication usage are required to address this issue.

Digital health systems have suddenly become a really promising way to turn healthcare delivery around in LMICs due to mobile connectivity, the ability to instantly share data and the boom of remote healthcare through telemedicine (Iyawa, Herselman, and Botha 2016). Digital infrastructures enable us to keep tabs on who is buying which medicines, monitor antibiotic use, and even provide remote clinical guidance to patients in underserved areas. But even though these systems can gather and organise health data, most don't have the analytical intelligence to figure out what a patient's symptoms mean and support clinical decision-making autonomously. By adding artificial intelligence (AI) to these digital platforms, we could finally turn them from data collectors into patient-centred decision-support tools.

Recent advancements in AI present a significant opportunity to enhance these digital infrastructures. Machine learning (ML) and large language models (LLMs) have demonstrated substantial potential to improve clinical decision-making through the analysis of both structured and unstructured health data (Esteva et al. 2017; Devlin et al. 2019; OpenAI 2023; Nori et al. 2023). Standard machine learning models, such as ensemble classifiers and gradient-boosted trees, are effective with structured clinical data and are easy to understand and use (Badawy, Ramadan, and Hefny 2023; Biswas et al. 2025). Transformer-based LLMs, like BERT (Devlin et al. 2019) and GPT-4 (OpenAI 2023), are effective at understanding medical narratives and finding subtle differences in the context (Bélisle-Pipon 2024; Anaissi, Braytee, and Akram 2024). Machine learning models require appropriately selected and constructed features and datasets. Computational cost, inconsistency, and potential bias frequently limit LLMs in clinical environments (Anaissi, Braytee, and Akram 2024; Yang et al. 2023; Thirunavukarasu et al. 2023).

In this study, we propose the development of a digital health system that collaborates with AI to improve healthcare in countries facing significant challenges. Our proposed framework for LMICs is a combination of two key elements: a digital platform that monitors prescriptions using structured data analysis and a symptom checker that uses a mixture of machine learning and large language models. A cloud-based solution integrates doctors, pharmacists, and policymakers, enabling them to monitor activities, remain informed, and receive real-time feedback.

Its main contributions are:

- **Implemented and Evaluated a Digital Prescription Tracking System:** A digital infrastructure linked to pharmacies that maintains records and monitors medicine purchases, maintains digital health accounts, and connects users with telemedicine counselling to ensure correct antibiotic use and adherence to prescribed courses. The system was deployed across multiple community pharmacies and evaluated through a real-world digital intervention, demonstrating measurable improvements in prescription compliance and a reduction in irrational antibiotic use.
- **Proposed an AI-Based Symptom Checker Framework:** A hybrid AI triage system combining machine learning (ML) and large language model (LLM) approaches that interprets symptom narratives. It predicts whether a patient requires a physician consultation or can be managed with over-the-counter (OTC) medication, serving as a decision-support module within the digital health ecosystem.
- **Integrated AMR-Reduction Framework:** A connected ecosystem linking pharmacies, doctors, and policymakers through real-time dashboards for antibiotic usage monitoring and behavioural change, directly targeting irrational antibiotic consumption and antimicrobial resistance (AMR) in LMICs.

Related Work

Antimicrobial resistance (AMR) has been extensively studied as a significant global public health issue, particularly affecting LMICs due to unregulated access to antibiotics and self-medication practices (World Health Organization 2014; O'Neill et al. 2018). Prior work has emphasized the role of community pharmacies in shaping antibiotic consumption behavior and highlighted the need for system-level interventions beyond policy and awareness campaigns (Morgan et al. 2011). Digital health interventions, such as pharmacy-based record systems and telemedicine platforms, have been explored to enhance access to care and encourage rational medication use in resource-limited environments (Labrique et al. 2020; Bashshur et al. 2020). While these approaches demonstrate benefits in monitoring prescriptions and facilitating clinician access, they typically rely on manual symptom assessment and do not provide automated decision support for triage at the point of care. In parallel, AI-based symptom checkers and clinical triage systems have been developed using traditional machine learning models trained on structured clinical data (Esteva et al. 2019; Topol 2019) as well as more recent large language model (LLM) approaches capable of processing unstructured patient narratives (Devlin et al. 2019; Alsentzer et al. 2019). Although these systems show promising predictive performance, most evaluations are retrospective, conducted on curated datasets, or disconnected from real-world healthcare workflows. Concerns regarding reliability, safety, and accountability have further limited their deployment in clinical settings. Recent research has highlighted the use of artificial intelligence techniques to process both structured clinical data and unstructured textual information in healthcare decision support systems (Jiang et al. 2017). However, empirical validation of such combined approaches in realistic patient scenarios and their integration with operational healthcare infrastructure, particularly in LMIC community pharmacy contexts remains limited.

Methodology

System Architecture

The integrated system architecture in Figure 1 establishes a unified digital–AI ecosystem to promote rational antibiotic use through pharmacy-linked interventions, automated triage, and centralized antimicrobial surveillance. Participants are divided into three groups after obtaining access to the system through community pharmacies: (i) those with valid prescriptions, (ii) those expressing symptoms but without prescriptions, and (iii) those seeking self-medication.

For patients with prescriptions, the digital platform records purchase details, verifies medicine authenticity through OCR-based data extraction, and tracks course completion. Those purchasing incomplete courses receive automated SMS reminders prompting them to buy the remaining doses.

For persons without prescriptions, the system engages the AI-driven symptom-checker module, which evaluates symptom descriptions to determine whether to recommend an over-the-counter drug or a telemedicine referral is required.

Patients who need an expert review are referred to registered online doctors for advice before they consume any antibiotics.

All data regarding symptom inputs, prescription tests, prescription information, and telephone consultation records are securely saved in a cloud repository and displayed on an administrative dashboard accessible to healthcare authorities and policymakers. This creates a continuous feedback loop connecting patients, pharmacists, telemedicine physicians, and regulators. The architecture facilitates a human-in-the-loop antibiotic stewardship framework that integrates clinical expertise, digital tracking, and AI-driven decision support to reduce irrational antimicrobial consumption at the community level. This integrated system consists of two primary components:

1. A Digital Intervention System, which has been developed and piloted to show measurable changes in behaviour and prescribing practices.
2. A Proposed AI-Based Symptom Checker, designed for future integration to enable automated triage and intelligent clinical decision support.

Digital Intervention System

The digital intervention implemented by CMED Health (CMED Health Ltd. 2026) with support from Bangladesh Medical University (BMU) (Bangladesh Medical University 2026) was deployed in selected community pharmacies across two areas of Dhaka. The intervention was evaluated through pre and post implementation phases to assess changes in antibiotic purchase behaviour. The system was developed to track medicine purchases in the community and to promote the proper and complete use of antibiotics.

The platform works through two connected mobile apps: an agent app that the pharmacist or health agent uses to keep track of sales and patient information, and a customer app that stores purchase history and sends reminder notifications. As explained earlier, the system keeps track of and records pharmacy-based interactions in real time through several different user pathways. A digital health account is generated automatically for every customer. This account retains personal information, including the names and quantities of purchased antibiotics. The pharmacist or health agent inputs this information using the mobile interface, which maintains a record of all dispensing activities and facilitates post-purchase follow-up.

The app calculates how many doses remain when a patient buys an incomplete course and sends an automated SMS reminder to complete the full treatment. When a customer needs professional advice, health agents can also use the same app to connect them with telemedicine doctors. This makes it less likely that people will use antibiotics inappropriately. At the pharmacy, short videos are shown to teach people about the dangers of antimicrobial resistance and the need to complete their antibiotic courses.

All sales and telemedicine data are transferred to a secure cloud database, where the information is combined and displayed on an administrative dashboard for regulators and policymakers. This dashboard enables real-time monitoring of antibiotic purchase trends, incomplete courses, and pharmacy-level compliance indicators. The digital intervention effectively demonstrated visible improvement in rational antibiotic use behaviour and currently serves as the operational foundation for implementing proposed AI-based symptom-checker models.

Table 1: Comparison of key antibiotic-purchase indicators before and after the digital intervention.

Indicator	**Phase-1**	**Phase-2**	**% Change**
Antibiotic among total medicines	23.05%	17.09%	↓26%
Self medicated antibiotic use	4.05%	0.86%	↓79%
Prescription based antibiotic use	8.38%	9.24%	↑10%
Medicines bought by name	53.57%	43.49%	↓19%

Pilot Evaluation and Key Outcomes

The digital intervention was divided into the pre-intervention and post-intervention phases. The digital system was implemented in 28 selected pharmacies in these two areas. Phase 1 (43 days) represented the baseline period, while Phase 2 (48 days) captured the post-intervention outcomes. Throughout the study period, the digital system recorded medication purchase data from 2,654 individuals across both phases.

To examine improvements in antibiotic purchasing behaviors, we evaluated transaction records from 3,295 purchases in phase 1 and 7,402 purchases in phase 2. Although the total number of medicines sold increased substantially during the post-intervention period, the normalized share of antibiotics declined sharply from 4.05 % to 0.86 % confirming a genuine behavioral improvement rather than a sampling artifact.

At the population level, the proportion of antibiotics among all purchased medicines decreased from 23.05% to 17.09%, representing a 26% relative reduction in antibiotic use. The intervention also produced notable shifts in purchasing patterns: medicines bought solely by name fell from 53.57% to 43.49%, while purchases supported by valid prescriptions rose from 27.6% to 43.5%. Table 1 shows the intervention results. These shifts indicate an increasing reliance among pharmacy clients on expert advice and telemedicine consultations facilitated by the digital platform.

Proposed AI-Based Symptom Checker

While this section presents the architecture and design rationale of the AI-based symptom checker, model evaluation details are reported in the Results section.

This section presents the proposed AI-based part of the integrated framework. It is designed to help pharmacists and patients make decisions and perform clinical triage. The symptom checker is an intelligent decision support module that is designed to work with the digital intervention system. It will work for people who have symptoms but don't have proper prescriptions. The main goal is to find out if the reported symptoms can be treated with OTC medication or if an authorized physician is required via telemedicine.

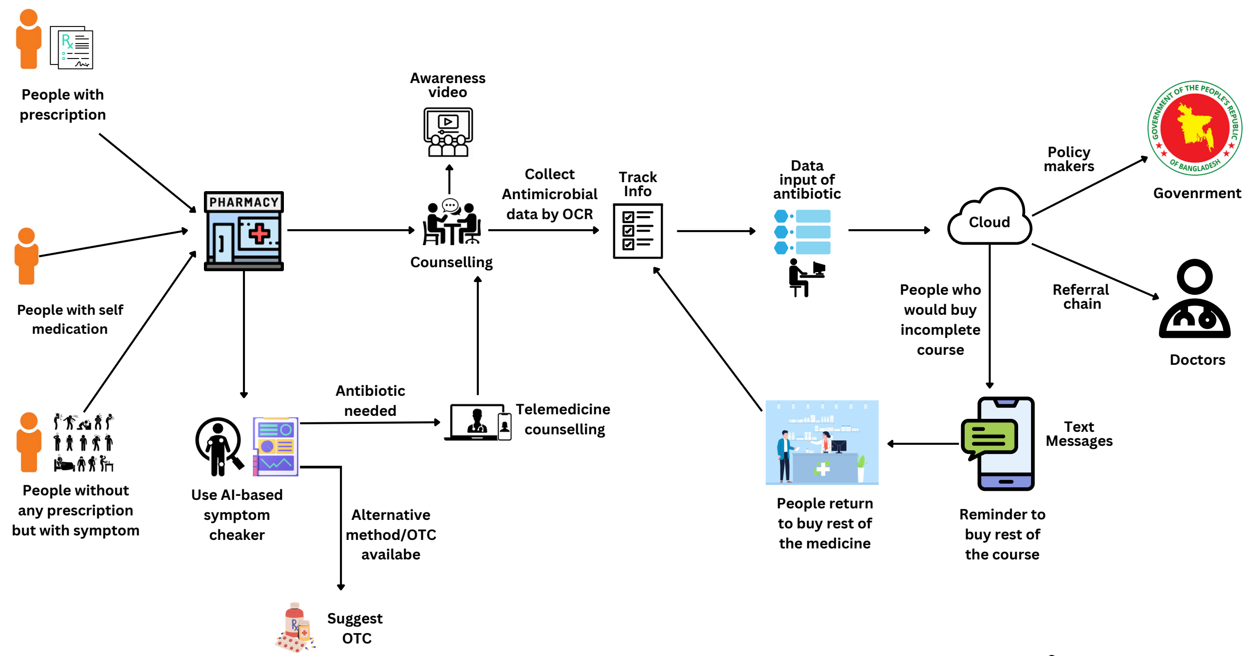

Figure 1: Overall system architecture of the integrated digital AMR reduction framework. The platform connects pharmacies, telemedicine doctors, and policymakers through a unified cloud-based network integrating prescription tracking, AI-driven symptom checking, and real-time antimicrobial data monitoring.

To achieve this, two complementary models are proposed an ensemble machine learning (ML) based symptom checker trained on structured, symptom-annotated datasets and a large language model (LLM) based symptom checker fine-tuned to interpret unstructured patient narratives. Both models are designed to operate within the same digital ecosystem, enabling context-aware triage, interpretability, and real-time integration with the pharmacy based digital system.

Dataset Description: The ML and LLM-driven symptom checker models are constructed on a large, structured dataset that was carefully curated and clinically validated primarily for this triage application. The dataset contains 131,345 patient cases, which cover a wide range of common clinical presentations that can be seen in primary care settings.

We created this dataset by gathering information from a range of trustworthy public sources, including national health information systems and clinical repositories. We focused on conditions that are common in LMICs like Bangladesh. Before being added, each record was standardized, cleaned, and de-identified. Then, a group of medical professionals reviewed it to make sure it was clinically valid. The dataset contains five key features, age, gender, symptom duration, symptom severity, and associated symptoms which together capture the essential clinical context for accurate triage. Table 2 shows these detailed attributes. The target label corresponds to the physician validated treatment recommendation, indicating whether the case requires a doctor consultation or can be managed with OTC medication.

Table 2: Dataset Description

Attribute	Type	Description
Gender	Categorical	Male, Female
Age	Categorical	Male: $\leq$5, 6–15, 16–60, >60 years; Female: $\leq$5, 6–15, 16–45, >45 years
Duration	Categorical	$\leq$3 days, >3 days
Symptoms	String	1,816 unique symptoms
Severity	Categorical	Mild: No interference with daily activities; Moderate: Some daily activities limited; Severe: Cannot perform any daily activities
Treatment	Categorical	Doctor consultation or OTC drug

Independent Evaluation Dataset: In addition to the dataset used for model development and training, the AI-based symptom checker was evaluated using an independently collected real-world dataset. This evaluation dataset was not used during training and was employed solely to assess standalone triage performance.

The ensemble ML model and the transformer-based LLM model both use this structured dataset as input. The ML model uses engineered numerical and categorical features, but the LLM module processes the same records in their unstructured text form, capturing narrative symptom descrip-

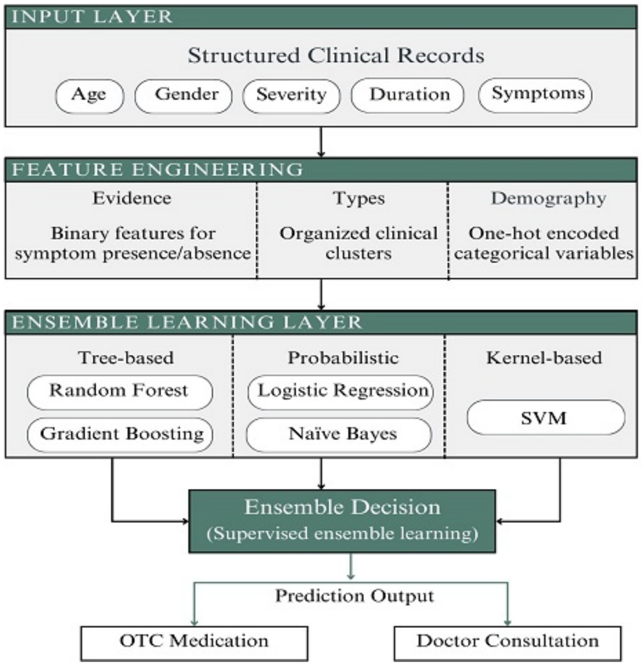

Figure 2: Architecture of the ML-based ensemble model symptom checker

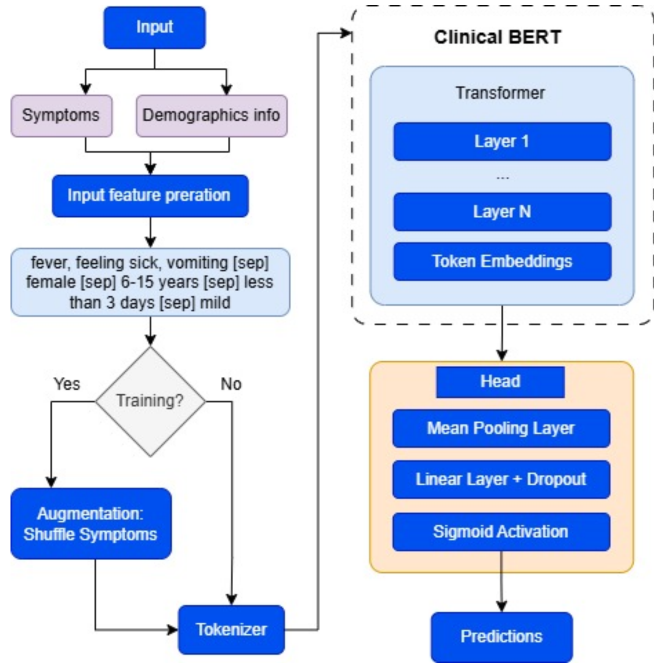

Figure 3: Architecture of the LLM-based symptom checker

tions for context. This dual representation makes sure that both models can use the same clinical knowledge while learning from different types of data.

ML Based Ensembling Approach: The machine learning based symptom checker uses a supervised ensemble learning method to figure out if a patient can manage their symptoms with OTC or if they need to see a doctor. The system has a lot of classifiers that help it generalize better and reduce the bias of each model. The ensemble is made up of tree-based models (like Random Forest and Gradient Boosted Decision Trees), probabilistic and linear models (like Logistic Regression and Naïve Bayes), and a kernel-based model (like Support Vector Machine). Figure 2 shows our propose approach

Feature engineering was used on the structured dataset to transform raw clinical records into the best inputs for model training. The processed data had three main sets of features:

- **Evidence of Symptoms:** Binary features indicating the presence or absence of each symptom.
- **Organized Symptom Types:** Broader clinical clusters (e.g., respiratory, gastrointestinal) formed by aggregating related symptoms to reduce dimensionality and identify disease-level patterns.
- **Encoded Demography:** Categorical variables including age, gender, symptom duration, and severity were transformed into numerical representations using one-hot encoding.

LLM Based Approach: This method allows the model to handle unstructured, narrative-style inputs instead of relying solely on predefined categorical features. In order to accomplish this, a few pretrained transformer backbones, like BERT and ClinicalBERT, were changed and improved for binary triage classification, which means deciding whether a patient needs to see a doctor or can be treated with an OTC drug. Figure 3 depicts our proposed approach.

Each structured patient record was turned into a textual clinical narrative using a template format with [SEP] tokens to separate the symptoms from the demographic information. The model broke these stories down into smaller pieces and cut them off at a set length so they could be processed quickly. During training, data augmentation was used to make the model more robust and less likely to overfit by shuffling comma-separated symptoms.

The architecture has three main parts: a transformer encoder that makes contextual embeddings from the input text, a mean pooling layer that combines these embeddings into a fixed-size representation, and a classification head that includes a fully connected layer with dropout regularization and a sigmoid activation function. The final output gives the chances of each triage class, which makes it possible for the digital health system to provide real-time decision support that is easy to understand.

Training and Optimization: All ML and LLM models were trained using the structured dataset described above. The dataset was split into training (80%) and a held-out internal test (20%) subset, and cross-validation was applied during model development to ensure robustness and prevent overfitting. Hyperparameters were optimized using standard grid search strategies for the base classifiers and fixed training configurations for the transformer-based models. Model training and hyperparameter optimization were completed prior to independent evaluation, and no model parameters

Table 3: Performance of Selected ML and LLM Models on Real-World Patient Cases

Model	Accuracy	Precision	Recall	F1-Score
Part A: ML Models				
Ensemble (Soft-Voting)	0.946	0.948	0.934	0.946
GBDT	0.930	0.880	0.930	0.910
Logistic Regression	0.880	0.840	0.870	0.850
Part B: Fine-Tuned LLMs (With Augmentation)				
BERT	0.810	0.573	0.526	0.519
ClinicalBERT	0.802	0.532	0.511	0.499

were adjusted based on the real-world evaluation dataset.

Results

Independent Evaluation of the AI-Based Triage Module:

This section presents the empirical performance of the AI-based symptom checker, which was implemented and evaluated independently from the digital pharmacy intervention described earlier. The objective of this evaluation is to assess the technical effectiveness of the machine learning (ML) and large language model (LLM) components for automated health triage. These results do not reflect operational deployment or causal influence on the pharmacy-based intervention outcomes. The AI-based triage module was evaluated as a standalone decision-support system using an independent real-world dataset consisting of 247 patient symptom narratives. These cases were collected prospectively from individuals seeking medication at community pharmacies and were not used during model training. Each case was independently reviewed by licensed physicians, and the final triage label was assigned based on majority consensus. For each case, models predicted whether physician consultation or over-the-counter (OTC) treatment was appropriate, with physician consensus serving as the reference standard, and performance was assessed using Accuracy, Precision, Recall, and F1-score.

A. Performance of ML-Based Triage Models

The performance of the ML-based triage models on structured clinical representations of patient cases is summarized in Table III (Part A). Among the evaluated models, the ensemble soft-voting classifier achieved the highest overall performance, with an accuracy of 94.6% and an F1-score of 0.946. The Gradient Boosted Decision Trees (GBDT) model also demonstrated consistently strong performance across all evaluation metrics. These results indicate that ensemble-based ML approaches are well-suited for structured symptom, demographic, and severity features, supporting their role as reliable back-end decision engines for automated health triage.

B. Performance of LLM-Based Triage Models

The performance of fine-tuned LLM-based triage models is reported in Table 3 (Part B). Across different transformer-based architectures, classification accuracy ranged from approximately 78% to 81%. Models trained with symptom-shuffling data augmentation consistently outperformed their non-augmented counterparts. While LLM-based models exhibited lower overall accuracy compared to the ML ensemble, they demonstrated the ability to effectively interpret unstructured, narrative-style symptom descriptions. This capability is particularly relevant in real-world triage scenarios where patient inputs are linguistically diverse and less standardized.

C. Comparative Analysis and Design Implications

The comparative results reveal a trade-off between predictive reliability and linguistic flexibility. ML-based models deliver superior performance when structured clinical features are available, whereas LLMs provide greater robustness in interpreting free-text symptom narratives. These findings empirically support a hybrid AI-based triage architecture, in which LLMs function as front-end interfaces for symptom understanding and ML models serve as back-end decision engines for final triage classification. It is emphasized that the AI-based triage module was evaluated independently in a standalone setting and was not integrated into the deployed digital pharmacy intervention at the time of evaluation. Accordingly, no claims are made regarding clinical outcomes, treatment delays, or reductions in antimicrobial resistance attributable to the AI component. The fully integrated AI–pharmacy system is proposed as future work.

Discussions

This study presents an integrated digital health framework for LMIC settings such as Bangladesh, combining a medicine purchase–tracking system, telemedicine services, and a proposed AI-based symptom checker to address irrational antibiotic use and antimicrobial resistance (AMR). The system enables patients to maintain digital health accounts, access telemedicine consultations when needed, and receive digital prescriptions from licensed physicians, while consolidating medical records to support informed decision-making and continuity of care.

The digital pharmacy intervention demonstrated a measurable impact on antibiotic stewardship. Antibiotics accounted for 23.05% of all medicines purchased during the pre-intervention phase, decreasing to 17.09% post-intervention. Self-medicated antibiotic use declined substantially from 4.05% to 0.86%, indicating that the intervention was effective in promoting more rational medicine use within participating community pharmacies.

In parallel, this work proposed and independently evaluated an AI-based symptom checker designed to support triage decisions within the broader digital health ecosystem. As reported in the Results section, the AI module was evaluated as a standalone decision-support system using real-world patient symptom narratives and physician consensus as the reference standard. Ensemble-based machine learning models demonstrated strong performance on structured clinical features, while large language models (LLMs) exhibited complementary strengths in interpreting unstructured, narrative symptom descriptions. Although the AI-based triage module was not deployed as part of the pharmacy intervention during the study period, these findings provide empirical evidence of its technical feasibility and potential utility in future integrated deployments.

The results support a hybrid design in which ML models function as reliable back-end decision engines and LLMs serve as front-end interfaces capable of handling linguistically diverse and non-standardized patient inputs an essential consideration in LMIC contexts. However, the AI evaluation reflects technical performance only and does not imply direct clinical impact, reduced treatment delays, or AMR outcomes at this stage.

Several limitations should be noted. The digital intervention was evaluated across a limited number of pharmacies, restricting generalizability. The AI-based triage module was assessed independently and offline rather than within a live clinical workflow. Operational challenges included variability in digital literacy, initial resistance from medicine sellers, and difficulties in data collection. These challenges were mitigated through pharmacist training and community awareness initiatives focused on telemedicine use and AMR education.

Overall, this study demonstrates the feasibility and early impact of a digital pharmacy–based intervention for antibiotic stewardship in LMIC settings, while providing independent empirical validation of an AI-based triage module intended to complement such systems. Future work will focus on full system integration, longitudinal assessment of clinical and AMR-related outcomes, and deployment at a larger scale.

Future Work

The present study demonstrates the viability and efficacy of a digital pharmacy-linked intervention to reduce irrational antibiotic use. The proposed integration of AI-driven symptom-checker models is still in the conceptual stage and will be the primary focus of future work. The next step is to integrate the ML- and LLM-based triage modules into the current digital infrastructure and test them to see how well they perform in the real world and how reliable they are in a clinical setting. Future deployments will also incorporate explicit safety and governance mechanisms, including clinician-in-the-loop oversight and continuous monitoring for potential mistriage, to ensure responsible use of the system in real-world clinical workflows.

Future development will focus on (i) gathering larger and more diverse symptom datasets to improve model generalization across different demographics and disease categories, (ii) testing human-AI collaboration within pharmacy and telemedicine workflows to ensure safety and usability, and (iii) incorporating adaptive feedback mechanisms that enable clinicians to dynamically refine model behavior in real time. This progression will facilitate the development of a more comprehensive, scalable, and reliable AI-assisted digital health ecosystem that aligns with global goals to reduce antimicrobial resistance (AMR).

Conclusion

This study introduced a pilot-tested digital intervention framework to mitigate irrational antibiotic use in community settings through pharmacy-linked data monitoring and behavioural reinforcement. The implemented system successfully demonstrated measurable reductions in self-medicated antibiotic purchases and an overall improvement in prescription adherence, highlighting the effectiveness of digital tools in promoting rational medicine use.

Based on these positive results, the study also proposed an AI-enhanced framework that integrates ML and LLM-based symptom checkers into the current digital infrastructure. These innovative modules will enable automated triage, improve diagnostic decision support, and make it easier for pharmacists, telemedicine doctors, and regulatory bodies to communicate. It is emphasized that the AI-based symptom checker was evaluated independently as a standalone module and has not yet been integrated into the deployed digital pharmacy system.

In future implementations, the fully integrated system will be expanded and tested with larger groups to assess its impact on both clinical and operational outcomes. The planned digital–AI ecosystem is a big step toward data-driven antibiotic stewardship. It provides a scalable, adaptable, and human-in-the-loop approach to combat antimicrobial resistance in LMICs.

Acknowledgement

This research was jointly supported by United International University (UIU) and Bangladesh Medical University (BMU). The experimental activities of this project were funded by the Institute for Advanced Research (IAR), and supported by the Higher Education Acceleration and Transformation (HEAT) project's Academic Transformation Fund (ATF), HEAT-UIU-13864. The authors also gratefully acknowledge CMED Health Ltd. for providing access to medical professionals and operational support that facilitated this research.

Ethical Statement

This study was approved by the Research Ethics Committee of United International University (UIU) under reference number IREB/2023/009. For all procedures involving human subjects, participants provided informed written consent after being fully informed of the study's nature, their right to withdraw, and the confidentiality of their data. The study also utilized publicly available health data that were fully de-identified prior to access and analysis. All personal identifiers were removed from all datasets before the research commenced to ensure strict anonymity and protect participant privacy.

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