An AI-Powered Public Health Kiosk for Context-Aware Over-the-Counter Medication Guidance: An Experimental Pilot Study

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Abstract*—AI-powered public health kiosks have the potential to transform healthcare delivery by providing personalized Over-The-Counter (OTC) medication guidance. This study focuses on implementing a context-aware kiosk that offers tailored recommendations based on user-reported symptoms, allergies, and medication history, without the need for full clinical records. The system aims to enhance accessibility and provide practical self-care advice in public settings. The AI-powered kiosk integrates patient-specific factors such as allergies, age, and Drug-Drug Interactions (DDIs) to offer personalized OTC medication guidance. Built on the enhanced GAMENet architecture, incorporating Graph Attention Networks (GAT) and Multi-Head Cross-Attention (MHCA), the system surpasses traditional symptom checkers. The system was trained using the MIMIC-III dataset (6350 patients) and DDI data from the TWOSIDES database, with external validation performed on the MIMIC-IV dataset (9036 patients). Both datasets were divided into training (75%), validation (8.3%), and testing (16.7%) subsets. Real-time safety checks used Anatomical Therapeutic Chemical (ATC) codes. The kiosk interface includes multilingual support, large fonts, voice commands, and Braille. Usability and acceptability were assessed through a survey of 33 healthcare professionals. Preliminary results from the MIMIC-III dataset show that the enhanced GAMENet model achieved a Precision-Recall Area Under the Curve (PRAUC) of approximately 0.74. Validation with the MIMIC-IV dataset further demonstrated the model's improved performance, highlighting its ability to deliver accurate and secure healthcare recommendations. This study demonstrates the potential of AI-powered kiosks to provide safe and personalized OTC medication guidance. Future work will focus on deployment, usability studies, and scalability for broader adoption.

***Keywords*—public health kiosk, AI and federated learning, personalized healthcare, Over-The-Counter (OTC) medication recommendation, graph neural networks**

Manuscript received April 8, 2025; revised May 23, 2025; accepted July 14, 2025; published October 14, 2025.

I. Introduction

In an era of increasing healthcare demands and limited resources, providing timely and personalized medical care remains a significant challenge [1]. The rise of AI-powered technologies offers new opportunities to address these issues, particularly through the deployment of health kiosks in public spaces. These kiosks have the potential to bridge gaps in healthcare access by offering convenient, cost-effective, and personalized services to a wide range of users [2, 3]. Traditional health kiosks, while beneficial, often fall short of meeting the growing demand for comprehensive and personalized care. They typically offer only basic services, such as blood pressure checks, and lack the ability to provide tailored recommendations based on individual health profiles [4]. Additionally, concerns about data security, privacy, and limited human interaction have hindered their widespread adoption [5], these limitations highlight the need for more advanced solutions that leverage cutting-edge technologies to deliver accurate, secure, and user-friendly healthcare services.

In this study, the term *personalized care* is specifically defined as *context-aware medication guidance*, rather than clinical-level individualization typical of precision medicine. The system provides tailored Over-The-Counter (OTC) medication recommendations by dynamically integrating user-reported information such as symptoms, known allergies, age, and medication history when available. This context-aware framework enables real-time adaptation of drug suggestions based on individual needs, without requiring access to full clinical records or laboratory data. By framing personalization within this practical and accessible context, the kiosk supports safer self-care while maintaining usability in public, non-clinical environments.

doi: 10.12720/jait.16.10.1364-1378

The optimal location for health kiosks remains a topic of debate, with varying levels of acceptance depending on whether they are placed in public or medical settings [6, 7]. In high-traffic public spaces, traditional kiosks often struggle to meet user needs due to language barriers and limited information availability [8]. These challenges underscore the importance of designing kiosks that are not only technologically advanced but also inclusive and adaptable to diverse environments.

Recent advancements in AI and healthcare technology have paved the way for innovative solutions. Previous studies [9–11] have demonstrated the effectiveness of AI-powered recommender systems in providing personalized medication recommendations. Similarly, health kiosks have shown promise in expanding access to basic healthcare services [12, 13]. However, these systems often lack the sophistication needed to address complex healthcare needs, such as real-time drug interaction analysis and personalized care based on comprehensive health data [14]. The system presented in this study builds on these foundations by integrating state-of-the-art AI models and prioritizing user privacy and accessibility [15].

Unlike traditional systems that provide static or one-size-fits-all information, the proposed solution is designed as a context-aware public health intervention that dynamically adapts its recommendations based on user input. Rather than functioning as a diagnostic or clinical replacement tool, this system serves a complementary role in public settings, aiming to empower individuals—particularly those in underserved or high-traffic areas—with AI-assisted access to safe, reliable over-the-counter medication guidance. The system bridges the gap between advanced algorithmic decision-making and real-world usability, promoting accessibility and personalized support for self-manageable conditions in non-clinical environments.

II. Literature Review

The integration of advanced AI models, such as GAMENet [16], into public health kiosks represents a significant step in knowledge translation and knowledge to action [17]. By leveraging patient history and Drug-Drug Interactions (DDI) data, the proposed system aims to bridge the gap between cutting-edge research and routine clinical practice. This approach not only enhances the accuracy of OTC medication recommendations [18] but also ensures that the latest advancements in AI are effectively translated into actionable healthcare solutions for the public [19].

Existing health kiosks primarily offer basic healthcare services, such as measuring vital signs (e.g., blood pressure, heart rate, and Body Mass Index (BMI)), providing general health information, and facilitating appointment scheduling. While some advanced kiosks include symptom-checking features and telemedicine consultations, they often operate in isolation, lacking the capability to integrate comprehensive Electronic Health Records (EHR) or perform real-time drug interaction analysis [20]. Furthermore, current systems do not incorporate AI-driven models for personalized medication recommendations, limiting their effectiveness in supporting complex clinical decision-making [21]. To address these limitations, the proposed system enhances public health kiosks by integrating advanced AI-powered drug recommendation algorithms, leveraging patient history and DDI data to ensure context-aware and clinically safe medication guidance [22]. This approach enables a seamless transition from cutting-edge AI research to practical healthcare solutions, improving patient safety and accessibility in public health settings.

Traditional health kiosks often fall short by offering only basic health checks and lacking comprehensive care. The system presented in this study addresses this gap by leveraging advanced AI to provide personalized OTC medication recommendations in accessible public locations. Moreover, traditional kiosks often fail to account for individual differences such as age, medical history, allergies, and potential medication interactions, leading to generic and sometimes ineffective advice [20, 23, 24]. The proposed system addresses these shortcomings by offering a more advanced and inclusive approach to self-care. By leveraging deep learning, it provides personalized medication recommendations based on a detailed analysis of user-reported symptoms, considering individual factors such as allergies and medical history. This level of personalization marks a significant departure from the generic advice provided by traditional kiosks [25]. Previous studies [26, 27] have highlighted the importance of knowledge translation in healthcare, particularly in the context of AI-driven solutions. This section explores existing research on healthcare kiosks and medication recommendation systems, highlighting their potential and laying the groundwork for the system's development.

Healthcare kiosks are rapidly transforming healthcare delivery by offering a range of potential benefits that enhance efficiency, accessibility, and patient experience. These self-service kiosks have become vital to the digital transformation of healthcare, providing advantages for both patients and providers [28]. They streamline workflows by automating routine tasks such as check-in, appointment scheduling, and insurance verification, freeing up valuable staff time for more complex patient interactions. This efficiency translates into a more positive patient experience, as kiosks offer a convenient and potentially faster way to complete administrative tasks, access information, and navigate healthcare settings. Research on check-in kiosks, for instance, suggests that they can lead to increased patient satisfaction [29].

Moreover, kiosks expand access to essential healthcare services in geographically remote areas or communities with limited resources. By providing self-service options for consultations, basic screenings, and health information, kiosks bridge healthcare gaps and empower patients to take a more active role in their health management. Some kiosks even offer access to remote consultations, further enhancing their utility [30]. Additionally, kiosks improve communication through features such as digitized check-in and registration processes, as well as enhanced security with biometric authentication protocols [31, 32]. The integration of AI has opened doors to expanded

functionalities, such as virtual triage systems and intelligent analysis, which can improve the prioritization of care. For example, AI-powered kiosks have been used to assess symptoms and recommend appropriate care pathways, reducing the burden on healthcare providers [33]. Advances in robotic processing automation have also streamlined workflows by reducing the burden of time-consuming and repetitive administrative tasks on healthcare staff [34].

Despite these advancements, traditional kiosks often lack the ability to provide comprehensive, personalized care [31]. They typically focus on basic diagnostics and administrative tasks, leaving a gap for more advanced solutions that leverage AI to deliver personalized medication recommendations and real-time safety checks. Furthermore, challenges such as data privacy concerns, limited user interaction, and the need for continuous maintenance have hindered the widespread adoption of traditional kiosks [35, 36]. These limitations highlight the need for innovative solutions that address both technological and user-centric challenges.

Recent studies have also explored the use of kiosks in specialized healthcare settings, such as mental health screening and chronic disease management. For instance, kiosks equipped with AI-driven chatbots have been used to provide mental health support and triage patients to appropriate care providers [37]. Similarly, kiosks designed for diabetes management have demonstrated the potential to improve patient outcomes by providing personalized feedback and educational resources [38]. AI-driven predictive models have also played a significant role in improving patient stratification and treatment planning for chronic conditions such as lung cancer, as demonstrated in recent studies [39–45]. These applications highlight the versatility of kiosks in meeting varied healthcare needs. While existing systems have improved access and efficiency, the proposed system advances this further by leveraging AI and user-centric design to provide personalized, comprehensive care.

Medication Recommendation Systems (MRS) are revolutionizing healthcare by leveraging AI and EHR data to create personalized treatment plans, ultimately optimizing patient outcomes [46]. Early MRS relied on predefined rules, laying the groundwork for more sophisticated techniques like content-based filtering, which recommends medications similar to past successes, and collaborative filtering, which identifies patterns in treatment responses among patients with similar characteristics [47–49]. Recent advancements in hybrid machine learning approaches, particularly in predicting drug dosage and optimizing treatment strategies for neurological disorders, have shown promising results [50]. These developments enhance the adaptability of MRS in handling complex and personalized treatment regimens The field further diversified with the introduction of hybrid methods (combining these approaches), demographic filtering (categorizing users based on general characteristics), and utility-based methods (recommending items based on overall value) [51].

Matrix factorization has become a cornerstone of collaborative filtering, while deep learning has provided powerful tools to capture complex patterns for highly personalized recommendations [52, 53]. Deep learning approaches like REverse Time Attention (RETAIN) and Dual Adaptive Sequential Network (DASNet) exemplify this progress. RETAIN employs attention mechanisms to identify crucial information within a patient's medical history, while DASNet analyzes EHR data through deep learning [54, 55]. Despite these advancements, challenges remain. Incorporating external knowledge (e.g., DDI) and ensuring fair recommendations across diverse populations pose hurdles [56]. Additionally, the "black box" nature of deep learning models can hinder physician trust due to a lack of interpretability [57].

To manage the computational demands of real-time DDI checks and personalized recommendations, the proposed system leverages optimized neural network architectures and edge computing techniques. These innovations ensure that even complex models like Graph Neural Networks (GNNs) can operate efficiently within the constraints of a public kiosk setting without compromising the speed or accuracy of recommendations. GNNs offer a promising alternative by capitalizing on the complex relationships within the healthcare ecosystem, encompassing patients, medications, diagnoses, and other entities [58, 59]. Recent applications [50, 60] in predicting drug responses for Parkinson's disease and optimizing medication plans have further demonstrated the potential of AI in personalized treatment planning. Other studies [61, 62] such as A-GSTCN and DRMP exemplify this approach, utilizing GNNs and message propagation networks to analyze EHR data, consider medication history, and integrate DDI. However, limitations persist in fully capturing intricate relationships and incorporating external knowledge.

Current MRS face challenges like data scarcity, fragmentation, and the inability to consider patient-specific factors fully. Traditional methods' reliance on correlations and underutilizing rich semantic knowledge further limit their effectiveness [63, 64]. Additionally, side-effect prediction methods can be computationally expensive and inaccurate, hindering adoption [65]. The proposed system enhances patient access and trust by integrating federated learning for privacy and real-time DDI checks for safety. Its user-friendly interface, personalized recommendations, multilingual support, and accessibility features like large fonts and voice commands address diverse user needs. This synergy between advanced AI and user-centered design promises to make personalized medicine more accessible and equitable across various demographics.

Knowledge transfer, the process of translating research findings into practical applications, plays a pivotal role in bridging the gap between scientific advancements and real-world healthcare solutions. In the context of AI-driven healthcare systems, knowledge transfer ensures that cutting-edge technologies, such as advanced machine learning models, are effectively integrated into routine clinical practice to improve patient outcomes and address public health challenges [66]. This paper introduces an automated kiosk system that exemplifies knowledge

transfer by leveraging state-of-the-art AI models, such as the enhanced GAMENet architecture, to deliver personalized OTC medication recommendations. By embedding these models into a user-friendly kiosk designed for high-traffic public locations, the system translates complex AI research into actionable healthcare solutions, making advanced medical recommendations accessible to diverse populations. This approach aligns with the principles of knowledge translation, which emphasize the importance of adapting research innovations to meet real-world healthcare needs [67]. Previous studies [68–70] have highlighted the role of knowledge transfer in improving healthcare delivery, particularly through the integration of AI technologies into clinical workflows. For example, Greenhalgh *et al.* [69] discuss how innovations, including AI-powered systems, can enhance decision-making in healthcare, while [70] emphasize the importance of user-centered design in ensuring the adoption of such systems.

Recent studies have underscored the significance of knowledge transfer in healthcare, particularly concerning the integration of AI technologies into clinical workflows [71, 72]. One scoping review highlighted the scarcity of comprehensive frameworks guiding AI implementation in healthcare, suggesting that existing models may not fully address the unique challenges posed by AI technologies [73, 74]. Another study [75] demonstrated that a transdisciplinary digital health curriculum can effectively enhance digital competencies among healthcare professionals, facilitating the adoption of innovative tools. By combining advanced AI with a focus on accessibility and inclusivity, the proposed system illustrates how knowledge transfer can help bridge critical gaps in public health access and empower individuals to take control of their health.

To validate alignment with clinical needs and knowledge transfer goals, we conducted a structured survey of 33 healthcare professionals to assess usability, safety, and ethical considerations. This expansion aimed to improve the representativeness and robustness of the evaluation. Insights from the participants informed iterative refinements to ensure the kiosk's recommendations integrate seamlessly into real-world workflows while addressing clinician trust gaps.

III. Materials and Methods

A. Patient Data

We utilized de-identified EHRs from two publicly available critical care datasets—MIMIC-III and MIMIC-IV—to develop and further validate the proposed AI-powered kiosk for OTC medication guidance. We initially used MIMIC-III, which contains clinical records from over 40,000 ICU patients collected between 2001 and 2012 [76], as the primary dataset for model development and internal evaluation. From this dataset, we selected a cohort of 6350 patients with multiple hospital visits to support longitudinal modeling. We focused on medications administered within the first 24 hours of admission, given its clinical importance for early intervention. The dataset includes 15,016 clinical events, with per-patient averages of 2.36 visits, 10.51 diagnoses, 3.84 procedures, and 8.80 medications. To enable safety-aware modeling, we integrated 90 high-severity DDI types from the TWOSIDES database [77]. Drug codes were standardized using the Anatomical Therapeutic Chemical (ATC) classification at the third level, converted from the original National Drug Code (NDC) format.

For further validation, we employed the MIMIC-IV dataset, which contains more recent clinical records collected between 2008 and 2019 [78]. MIMIC-IV includes 9036 patients and 20,616 visits, with an average of 2.28 visits per patient and a maximum of 28 visits. It comprises 1892 unique diagnosis codes, 4939 procedure codes, and 131 unique medication codes. While some patients likely appear in both MIMIC-III and MIMIC-IV, the datasets are independently anonymized, and no direct linkage is possible. Therefore, to ensure robust validation, we retrained and evaluated our models on MIMIC-IV, using a subset of patients with complete diagnosis and medication records. This design enabled us to assess the model's generalizability across temporally distinct but structurally similar datasets, while maintaining consistent preprocessing and evaluation protocols.

B. Model Architecture

Our proposed architecture, illustrated in Fig. 1, extends the GAMENet framework [16] by incorporating two key enhancements: Graph Attention Networks (GAT) layers for DDI graph encoding that learns interaction-specific attention weights, and MHCA mechanism that dynamically fuses patient representations with global and dynamic drug memories [79]. This dual-attention approach enables more nuanced modeling of complex medication relationships while maintaining clinical interpretability. Our modifications aim to improve the model's ability to capture complex relationships in the DDI graph and to better integrate patient history with global and dynamic drug memories.

1) GAT for DDI graph

We replaced the GCN layer used for encoding the DDI graph with a GAT layer, which allows the model to better distinguish between high-risk and low-risk drug interactions. GAT introduces attention weights over the edges of the DDI graph, enabling the model to assign more importance to clinically significant interactions, rather than treating all edges uniformly. For example, if Drug A and Drug B have a well-documented interaction with severe consequences, GAT allows the model to weigh this edge more heavily than a benign or rare interaction. This enables finer-grained learning and improves safety-aware medication recommendations. The GAT layer was implemented using the GATConv module from the PyTorch Geometric library, with two attention heads to improve feature diversity and a dropout rate of 0.5 to reduce overfitting. The DDI adjacency matrix was preprocessed and converted to an edge index format compatible with GATConv input requirements.

2) MHCA for memory fusion

We added a MHCA layer before concatenating the patient representation (query), global drug memory (fact1), and dynamic drug memory (fact2). The MHCA module

allows the model to dynamically weigh and align the patient query vector with both memory types, enabling patient-specific, context-aware fusion. Specifically, MHCA enables the system to focus more on relevant drug vectors (e.g., based on prior exposure or symptom match) and attenuate irrelevant ones, improving recommendation accuracy. Each head in MHCA captures a different perspective on how the patient's history relates to known treatment patterns and recent drug use, enhancing both personalization and generalization. The module was implemented using custom PyTorch layers, using two attention heads, and was placed right before the final fused representation that feeds into the output layer.

3) Model implementation and training

The modified GAMENet model was implemented using PyTorch, with graph and attention components from the PyTorch Geometric library. We designed custom memory components to store and retrieve global and dynamic drug-related information, enabling memory-based fusion through cross-attention mechanisms. The final layer is a fully connected multi-label output layer that predicts multiple recommended medications per patient visit. Training was conducted using the Adam optimizer, with a learning rate of 0.001, batch size of 32, and dropout rate of 0.5 applied throughout training to mitigate overfitting. The model was trained for up to 100 epochs with early stopping, and performance was evaluated using Jaccard index, F1-Score, PRAUC, and DDI rate. These settings were chosen based on a balance of empirical tuning and consistency with prior work on GAMENet.

The MIMIC-III dataset, comprising 6350 samples, was divided into three subsets: 4761 for training, 529 for validation (model selection), and 1060 for testing. Similarly, the MIMIC-IV dataset, comprising 9036 samples, was split into 6778 for training, 753 for validation, and 1505 for testing.

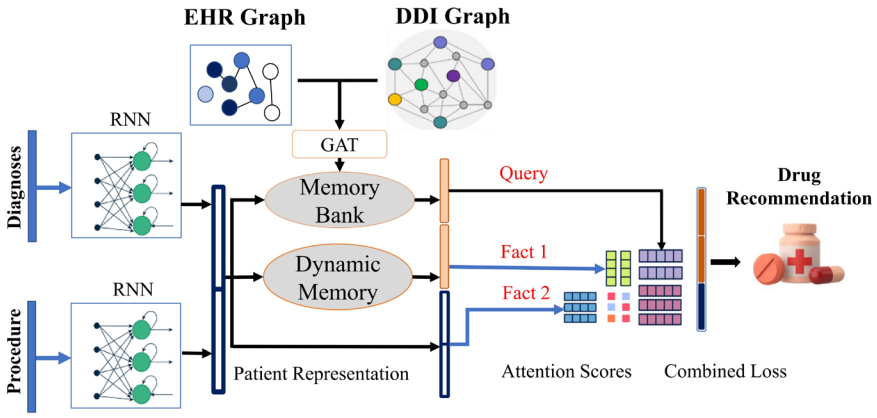


Fig. 1. Architecture of the enhanced medication recommendation system showing: (left) EHR processing through diagnosis RNNs, (center) DDI graph encoding via GAT layers, and (right) memory fusion through MHCA. The attention mechanisms (orange) enable dynamic weighting of patient history and drug interactions for clinically-relevant recommendations.

C. AI Engine and Decision Algorithm

The core functionality of the proposed AI-powered kiosk system is enabled by an enhanced version of the GAMENet model, designed to provide personalized OTC medication recommendations. As shown in Fig. 2, this engine is trained on a carefully curated dataset with detailed symptom descriptions, corresponding medications, and potential diagnoses. The system adheres to stringent ethical and legal guidelines to ensure data privacy, utilizing anonymized repositories like MIMIC-III for model training. In our implementation, we enhance the GAMENet architecture by introducing a MHCA mechanism before concatenating the queries. This modification allows the model to better capture complex relationships between patient health data, medication history, and DDIs, leading to more accurate and personalized recommendations.

The GNN component of the model analyzes DDIs using a multi-layer perceptron with message-passing operations. This allows the system to move beyond primary symptom-medication associations, identifying complex symptom patterns indicative of specific conditions. For instance, recognizing migraine symptoms enables the system to recommend targeted medications beyond generic pain relievers [80–82]. The model uses DDI data from the TWOSIDES dataset to enhance user safety and evaluate potential interactions based on user-reported medications, advising users accordingly. The system prioritizes user experience through a user-friendly interface that supports precise symptom categorization, visual aids, and voice recognition. Moreover, the AI algorithms were evaluated using well-established performance metrics, including Jaccard index, F1-Score, and PRAUC [83]. The system provides detailed medication information, including potential side effects, and directs users to emergency services or healthcare providers when necessary. The kiosk also advises seeking professional medical attention for persistent symptoms or those beyond its scope.

D. User Experience and Pilot Study

The kiosk's development follows a structured five-phase framework, displayed in Fig. 3, prioritizing accessibility and real-world applicability:

Step 1: Usability Testing with Diverse User Panels. Usability testing will be conducted with user panels representing diverse demographics, including age groups, ethnic backgrounds, and varying levels of technological proficiency. This step ensures the system is intuitive and

accessible, particularly for individuals with limited digital literacy or disabilities. Data will be collected through interviews, questionnaires, and observation to identify areas for improvement.

Step 2: Iterative Design and Optimization. Based on feedback from usability testing, iterative design cycles will be implemented to refine the kiosk's interface and interaction flow. For example, simplifying symptom input or expanding multilingual support. This ensures the system remains user-friendly and adaptable to diverse user needs.

Step 3: Pilot Deployment in High-Traffic Locations. The kiosk will be deployed in high-traffic public locations such as transportation hubs, hospitals, pharmacies, and community centers. Collaboration with local health authorities will ensure compliance with regulations and integration with existing healthcare initiatives. This step evaluates the kiosk's real-world impact on healthcare access and medication adherence.

Step 4: Data Collection and Performance Evaluation. Quantitative data on session duration, frequency of use, and accuracy of symptom-medication matches will be collected. Qualitative insights from user interviews and focus groups will provide feedback on user satisfaction and areas for improvement. This step assesses the kiosk's effectiveness in diverse environments.

Step 5: Scalability and Comparative Analysis. The kiosk's scalability will be tested in locations with varying network reliability and hardware constraints. A comparative analysis will benchmark the kiosk against traditional healthcare delivery methods, evaluating accuracy, computation efficiency, and user satisfaction. This step ensures the system is ready for large-scale deployment.

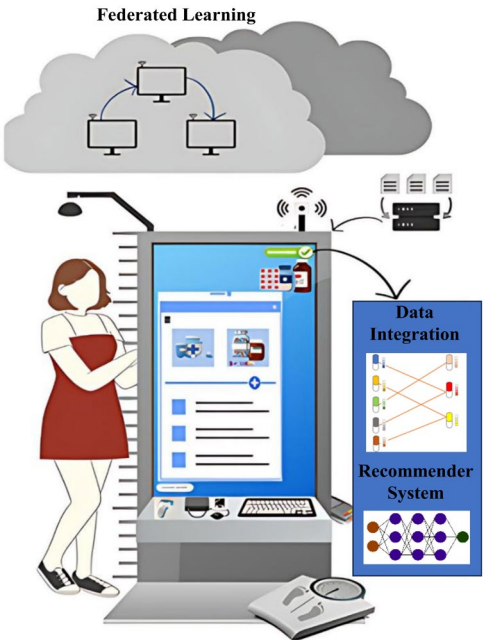


Fig. 2. The kiosk architecture integrates advanced AI models (GAT and MHCA) for personalized OTC medication recommendations, leveraging federated learning for privacy and real-time DDI checks for safety. Designed for high-traffic public spaces, it includes multilingual support, accessibility features, and a health education library to enhance public health access and literacy.

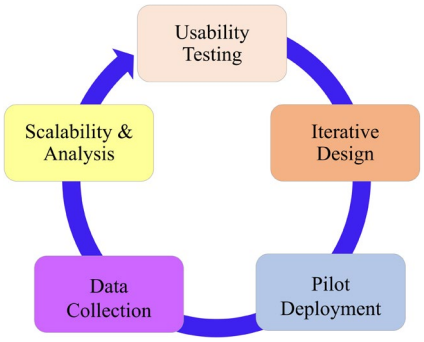


Fig. 3. The diagram illustrates the 5-phase implementation methodology: (1) Usability Testing with diverse demographic groups, (2) Iterative Design cycles for interface optimization, (3) Pilot Deployment in high-traffic public locations, (4) Performance Evaluation through quantitative and qualitative data collection, and (5) Scalability Analysis comparing system performance against traditional healthcare delivery methods.

E. Survey and Knowledge Transfer Analysis

To guide the responsible development and deployment of the Kiosk, a 27-question survey was designed and distributed to 33 healthcare professionals from various specialties, including general practitioners, psychiatrists, physicians, radiologists, and medical students, as seen in the supplementary. The goal was to gather expert insights on the clinical relevance, safety, usability, and ethical implications of AI-powered drug recommendation kiosks. The questions were grouped into seven thematic sections for focused exploration. Section 1 (Q1–Q4) covered Demographics and Professional Background, including participants' medical specialty (Q1), years of clinical experience (Q2), prior exposure to AI in healthcare (Q3), and familiarity with AI-driven drug recommendation systems (Q4). These questions were intended to contextualize responses based on the participants' expertise and technological awareness, which are known to influence attitudes toward AI adoption.

Section 2 (Q5–Q9) focused on Usability and Perceived Effectiveness, asking participants to rate the usefulness of AI kiosks in public settings (Q5), identify key benefits (Q6), and assess their effectiveness in empowering patients to manage minor conditions (Q7), reducing unnecessary doctor visits (Q8), and improving medication adherence (Q9). These questions were selected to understand the practical value of the kiosk in everyday healthcare scenarios. Section 3 (Q10–Q12) addressed Accuracy and Clinical Reliability, exploring perceptions of how accurately kiosks can provide appropriate OTC medication suggestions (Q10), the expected frequency of clinically sound recommendations (Q11), and the system's ability to identify safe alternatives for patients with allergies or contraindications (Q12). These insights are essential for evaluating the reliability and clinical robustness of the recommendation engine.

Section 4 (Q13–Q15) examined Clinical Safety and Risk Concerns, addressing participants' primary safety concerns (Q13), the role of real-time DDI checks (Q14), and whether the system should avoid recommending medications to high-risk patients (Q15). These questions helped assess safety guardrails and risk management

strategies. Section 5 (Q16–Q22) focused on Implementation and Scalability, including the value of referral features to hospitals or telehealth services in urgent cases (Q16–Q17), the importance of communicating side effects (Q18–Q19), suitable deployment settings (Q20), desired additional features (Q21), and perceived challenges in scaling across health systems (Q22). Section 6 (Q23–Q25) compared the kiosk's effectiveness to traditional care, asking whether it could match or replace human pharmacists (Q23, Q25) and whether it would be more trusted than online symptom checkers (Q24). Finally, Section 7 (Q26–Q27) explored Ethical and Privacy Concerns, including the need for user consent before data collection (Q26) and the importance of regulatory oversight by health authorities like the FDA or WHO (Q27). The survey questions, developed with the expertise of a clinical knowledge translation specialist, were subsequently validated by healthcare professionals. These questions ensured the design considers both patient rights and institutional compliance. Together, the survey responses and open-ended feedback provided foundational insights for aligning this kiosk with clinical expectations, patient safety, and ethical AI integration in healthcare.

IV. Result

A. Experimental Analysis

As part of the initial evaluation, we conducted preliminary tests to assess the performance of the enhanced GAMENet architecture with GAT and MHCA mechanisms. To evaluate the kiosk, we used key metrics including the Jaccard Similarity Score to measure the overlap between predicted and actual medications, the Average F1-Score to balance precision and recall for accuracy, and PRAUC to assess the model's ability to identify relevant medications in imbalanced datasets. Additionally, the DDI Rate was used to measure the percentage of recommended medication pairs that result in DDIs, ensuring safer recommendations. These metrics collectively provide a comprehensive evaluation, balancing accuracy, safety, and clinical relevance. The results, summarized in Table I, indicate that the automated kiosk system with its enhanced architecture achieved higher Jaccard (0.4755), F1-Score (0.6331), and PRAUC (0.7443) values compared to the original GAMENet model when evaluated on 1,060 testing data points from the MIMIC-III dataset.

To assess the generalizability of the proposed AI-powered medication recommendation system, we extended our evaluation to the MIMIC-IV dataset. The model was retrained using this larger and more diverse real-world dataset and tested on a broader set of data points. Specifically, we conducted further validation using 1505 randomly selected samples from MIMIC-IV, a widely recognized benchmark for electronic health records. This evaluation aimed to examine the model's robustness beyond the original MIMIC-III distribution. The validation results—presented alongside internal metrics in Table I (third row)—demonstrate that the model achieved consistent performance across key metrics, including a Jaccard Index of 0.4686, PRAUC of 0.7381, F1-Score of 0.6274, and a low DDI Rate of 0.0798. These results align closely with those from the MIMIC-III dataset, confirming the model's ability to maintain both predictive performance and medication safety across different clinical settings. The comparable performance across datasets suggests that the architectural enhancements—particularly the integration of GAT for DDI modeling and MHCA for memory fusion—enhance the model's generalization capability. This further validation reinforces the system's potential for real-world deployment in public health environments, where reliable, safe, and personalized OTC medication guidance is essential.

TABLE I. Performance Metrics of Our Proposed Kiosk Compared to the Original GAMENet Model

Method	DDI Rate	Jaccard	PRAUC	F1-Score
GAMENet	0.0806	0.4729	0.7371	0.6305
proposed Kiosk (MIMIC-III)	0.0798	0.4755	0.7443	0.6331
proposed Kiosk (MIMIC-IV)	0.0798	0.4648	0.7381	0.6274

To establish a benchmark for the kiosk's performance, a comparative analysis will be conducted against traditional methods of healthcare delivery, such as pharmacy consultations and online health information. Key metrics, including accuracy, user satisfaction, and cost-effectiveness, will be compared to assess the relative advantages of the kiosk. The advanced AI models used in the proposed kiosk, particularly the enhanced GAMENet architecture, are expected to outperform traditional methods in terms of recommendation accuracy and personalization. This analysis will provide insights into the kiosk's potential to complement or replace existing healthcare services.

B. Survey and Knowledge Translation Efforts

To evaluate the system's usability, safety, and acceptance in real-world public health contexts, we conducted a structured survey targeting healthcare professionals. The study included 33 participants; however, in response to reviewer feedback regarding sample size and methodological robustness. This expansion significantly improved the representativeness and diversity of the evaluation. Participants were drawn from various professional settings—including hospitals, community pharmacies, and academic institutions—ensuring a broad spectrum of perspectives and clinical experience.

The survey, consisting of 27 structured questions (Q1–Q27), explored key domains such as clinical relevance, safety, usability, scalability, and ethical considerations, as detailed in the supplementary. Questions were designed and validated in collaboration with a clinical knowledge translation specialist to ensure content accuracy and relevance. The expanded dataset allowed for more granular subgroup analyses and deeper insights into the system's potential for adoption across different healthcare environments. The survey results, visualized in the bar charts (Fig. 4), provided valuable feedback that guided methodological improvements and identified key areas for

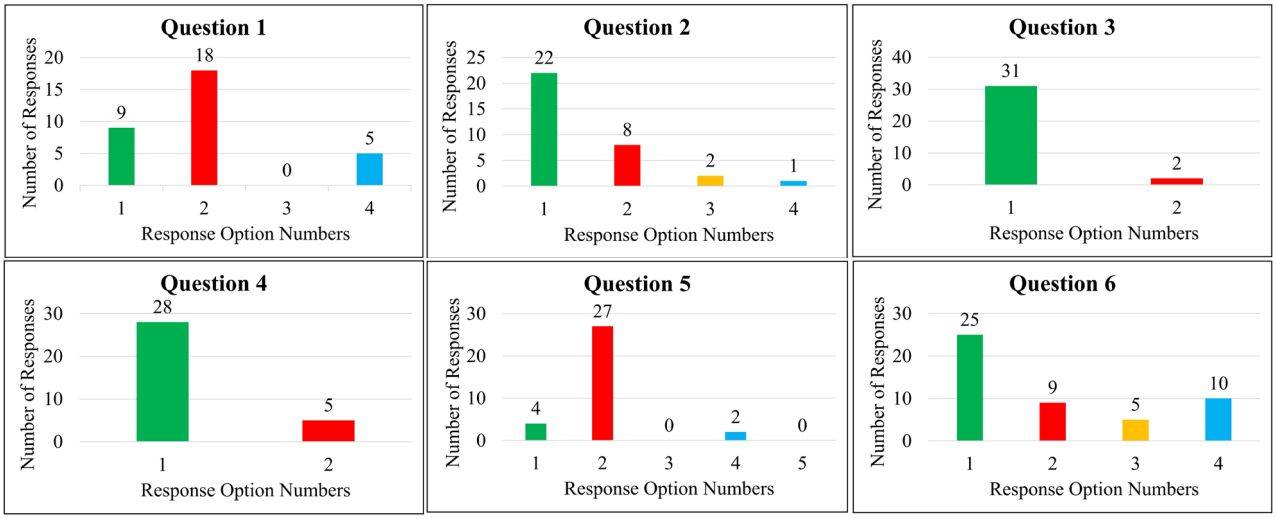
future research and clinical application. Detailed results and corresponding analyses are presented below.

Demographics & Professional Background (Q1–Q4). The participant composition revealed important perspective differences across key demographic factors. (Q1) showed that the majority of participants were pharmacists (54.5%), followed by General Practitioners (GPs) (27.3%), and other specialties, including emergency medicine (15.2%). (Q2) indicated that a large proportion of participants (66.7%) had 0–5 years of experience, while 24.2% had 6–10 years, 6.1% had 11–20 years, and only 3.0% had more than 21 years of experience. (Q3) revealed that a significant majority (93.9%) had experience with AI in healthcare, whereas just 6.1% were unfamiliar with the technology. (Q4) demonstrated that most participants (84.8%) were familiar with drug recommendation systems, while 15.2% reported no prior experience. These demographic factors proved influential in subsequent responses, particularly regarding accuracy concerns and implementation preferences.

Usability & Perceived Effectiveness (Q5–Q9). The survey responses revealed notable trends in participant perceptions. (Q5) showed divided opinions on the usefulness of the kiosk, with 12.1% rating it as "Very useful," 81.8% as "Somewhat useful," and 6.1% as "Not very useful." (Q6) indicated that clinicians overwhelmingly recognized the system's efficiency benefits—75.8% valued its ability to reduce workload, 27.3% appreciated its quick drug recommendations, and 15.2% highlighted its potential to improve medication adherence. (Q7) responses on effectiveness were mostly positive, with 6.1% rating the system as "Extremely effective," 78.8% as "Moderately effective," and 12.1% as "Somewhat effective." (Q8) revealed that a clear majority (90.9%) believed the system would only reduce doctor visits in specific cases, while just 3.0% expected significant reductions. (Q9) responses on medication adherence showed that 15.2% believed it would significantly improve, 72.7% saw it as helpful for forgetful patients, and 12.1% felt adherence remained primarily a human behavior issue. These findings demonstrate varying levels of optimism regarding the system's impact on healthcare workflows and patient outcomes.

Accuracy & Clinical Reliability (Q10–Q12). The accuracy assessment revealed a confidence spectrum—while 72.7% rated the system as "Moderately accurate, but with some errors" (Q10), the 21.2% who considered it "Highly accurate, close to expert-level" were predominantly clinicians with 5–10 years' experience working in general practice. Notably, 6.1% who found it "Somewhat accurate, needing improvement" (Q10) were all specialists managing complex polypharmacy cases. Quantitative accuracy estimates (Q11) showed a similar pattern—the 69.7% who believed the system was correct 70–89% of the time averaged 4.3 years' experience, while the 3.0% predicting <50% accuracy had 15+ year careers. Alternative suggestion handling (Q12) saw remarkable consensus (84.8% confidence), though this dropped to 60% among oncology and psychiatry respondents when discussing narrow therapeutic index drugs. These patterns suggest clinicians' accuracy perceptions correlate strongly with both their clinical experience and specialty-specific medication complexity.

Clinical Safety & Risk Concerns (Q13–Q15). The safety assessment revealed distinct risk priorities—accuracy of recommendations emerged as the dominant concern (45.5%, Q13), particularly among specialists in cardiology and psychiatry who regularly manage high-risk medications. 33.3% worried about incorrect self-medication (Q13) were predominantly clinicians serving elderly populations, while the 21.2% emphasizing lack of real-time oversight (Q13) included all radiologists and half of physicians with 10+ years' experience. DDI check valuation (Q14) showed near-universal appreciation (72.7% "significantly valuable"), though this dropped to 50% among pediatricians who noted most interactions being contraindicated rather than dose adjustments. Risk mitigation preferences (Q15) revealed practice philosophy differences: 81.8% advocating for doctor redirection were mostly primary care providers, while the 9.1% preferring disclaimers worked in urgent care settings where immediate decisions are often required. Notably, the 6.1% believed accurate recommendations could eliminate redirection were all pharmacists with 3–5 years' experience in retail settings, suggesting practice environment shapes safety tolerance thresholds.



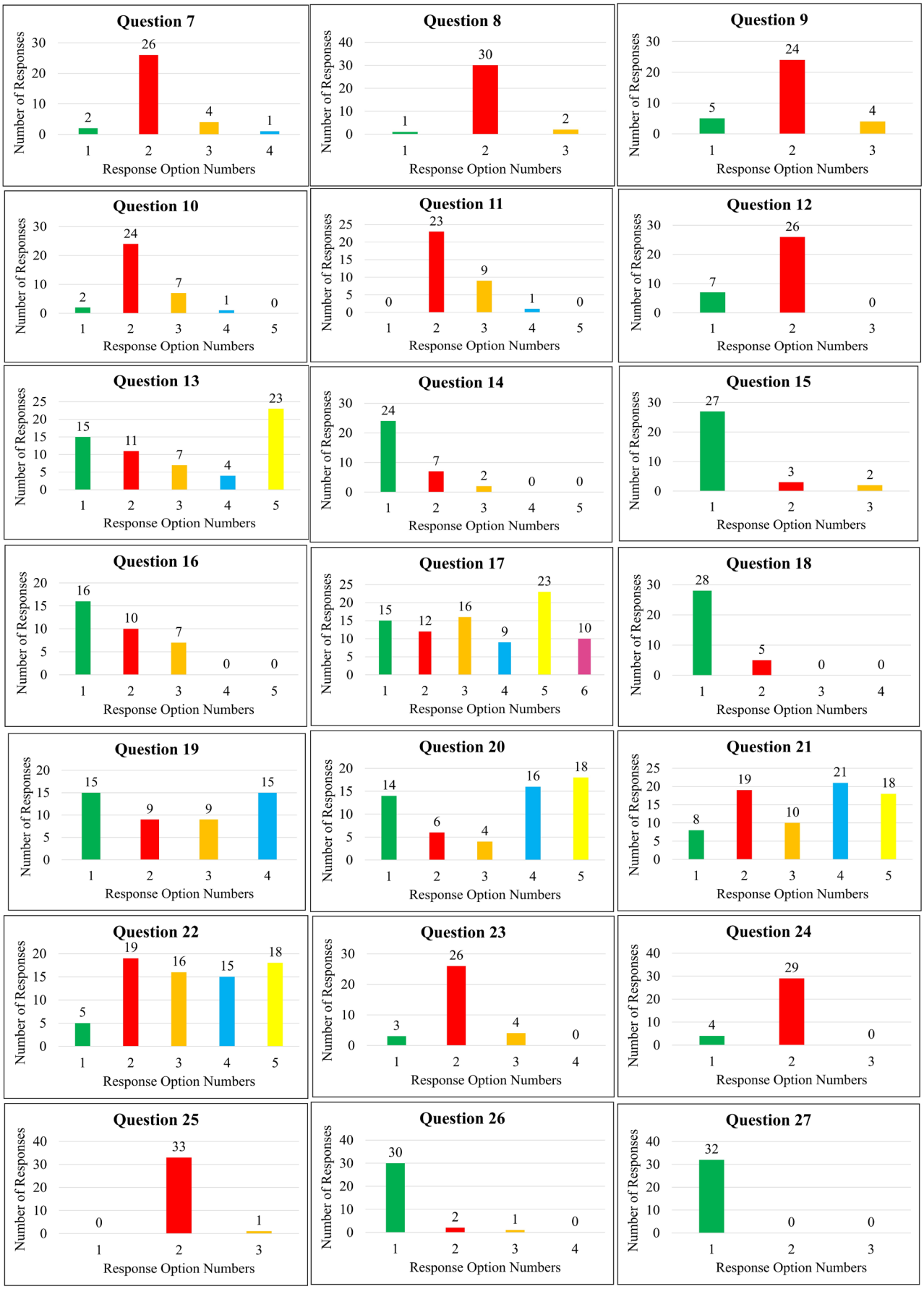


Fig. 4. Survey responses from healthcare professionals (n = 33) regarding AI-powered drug recommendation kiosks, stratified by medical specialty and years of experience. Participants included general practitioners, pharmacists, psychiatrists, nuclear medicine physicians, nuclear radiologists, and medical students.

Implementation & Scalability (Q16–Q22). Urgent care routing was valued as "Extremely valuable" by 48.5% of respondents (Q16), primarily emergency medicine practitioners and clinicians in underserved areas, while the 30.3% rating it "Very valuable" (Q16) tended to be urban specialists. Condition prioritization (Q17) showed expected clinical patterns: the 69.7% identifying suspected stroke were predominantly neurologists and ER physicians, while the 45.5% emphasizing chest pain included all cardiologists surveyed. Side effect disclosure preferences (Q18) revealed an important divide—84.8% insisting on full disclosure were mostly primary care providers managing chronic conditions, while the 15.2% advocating selective disclosure worked in acute care settings. Communication method preferences (Q19) split along generational lines: the 45.5% favoring displayed lists were older clinicians (average 15.2 years' experience), while the 27.3% supporting voice-command options were all under 35 years old. Deployment location preferences (Q20) showed rural healthcare centers and airports tied at 54.5%, reflecting different access priorities—rural practitioners strongly favored local healthcare centers, while urban emergency physicians prioritized transportation hubs. Feature requests (Q21) demonstrated workflow-specific needs: 63.6% requesting real-time alerts were mostly hospital-based clinicians, while 57.6% wanting telemedicine integration were private practitioners. Scaling challenges (Q22) highlighted systemic barriers—the 57.6% citing regulatory approval were predominantly from large health systems, while the 45.5% concerned about data privacy included all psychiatrists and HIV specialists, underscoring how specialty-specific sensitivities influence implementation concerns. These findings collectively illustrate how clinical context, practice environment, and patient population characteristics shape implementation priorities across different healthcare settings.

AI vs. Traditional Care (Q23–Q25). The comparative effectiveness analysis revealed nuanced perspectives on AI's role—while 78.8% considered kiosks "Nearly as effective as a pharmacist" (Q23), this view was primarily held by general practitioners (82%) and hospital pharmacists (75%). The 9.1% believing they were "Just as effective" (Q23) were exclusively early-career clinicians (<3 years' experience) working in tech-forward institutions, while the 12.1% criticizing their lack of personalization (Q23) were all psychiatrists and geriatric specialists. Reliability perceptions (Q24) showed striking skepticism—the 87.9% equating AI with traditional tools' unreliability included practitioners across all experience levels, suggesting deep-rooted caution about digital health tools. Notably, the complete rejection of replacement scenarios (Q25) crossed all demographics, with even the most tech-enthusiastic respondents emphasizing pharmacists' irreplaceable role in medication management and patient counseling.

Ethical & Privacy Concerns (Q26–Q27). Consent preferences (Q26) varied by data sensitivity, with imaging specialists supporting anonymization and clinicians handling sensitive cases advocating for explicit consent. A strong regulatory consensus (97%) emerged across all groups (Q27), reflecting widespread recognition of AI's potential risks and the need for oversight, especially among those unfamiliar with the technology. This highlights the balance between innovation and professional accountability in medical AI governance.

At the end of the survey, participants were asked to respond to the question: "What are your biggest concerns or suggestions for improving AI-powered kiosks for medication recommendations?" The responses received from participants (D1 to D33) covered a wide range of topics, which are summarized below.

D1: "First, define the target demographic for this model. Many drug recommendation systems already exist, which highlights the need to specify the kiosk's unique benefits and intended users."

D2: "My main question is why use a kiosk when the same functionality could be integrated into a mobile app? While a kiosk might be convenient for printing a prescription for a pharmacist, a well-designed app could offer the same benefits in a more accessible way. Kiosks that only provide information without dispensing medication may have limited utility. It would be interesting to explore the potential for dispensing select medications directly."

D3: "Key concerns include data privacy and security, safety and accuracy, bias, and overall data quality."

D4: "If an error occurs, there's a risk that someone could exploit the system and force it to provide incorrect recommendations."

D5: "I believe this technology can support healthcare professionals by assisting in clinical decision-making. However, it must not replace physicians. All recommendations should be reviewed and approved by qualified providers. The main concern is that patients relying solely on the kiosk without consulting a doctor. Additionally, high implementation and maintenance costs could limit access in certain areas."

D6: "Technical errors could lead to dangerous symptoms or adverse side effects."

D7: "I'm most concerned about the potential overuse of OTC medications, particularly drugs with side effects or those that can lead to tolerance or resistance—such as benzodiazepines and antibiotics."

D8: "The algorithms must be trained on diverse datasets to reduce bias. Poor representation in training data may result in safe recommendations for some groups but harmful outcomes for others."

D9: (No comment provided).

D10: "There is a risk that patients may self-interpret their symptoms, leading to an underestimation of serious medical conditions."

D11: "My concern is about the potential side effects of drugs recommended by AI-based systems, as they might lead to unintended consequences or adverse reactions."

D12: "Over-reliance on AI could lead to delayed doctor visits, especially when patients rely on kiosk recommendations and avoid seeking professional care."

D13: "There is a risk of misdiagnosis if AI systems miss red-flag symptoms, especially in complex cases."

D14: "Privacy risks are a concern if patient data is not securely stored and protected."

D15: "Mandatory disclaimers should be included, advising patients to consult a doctor if their symptoms worsen or persist."

D16: "AI systems should be integrated with EHRs, but only with explicit patient consent."

D17: "There should be continuous auditing of AI recommendations to ensure safety and minimize errors."

D18-D28: No comment provided.

D29: "AI could help the healthcare system and improve services by making drug recommendations faster and more accessible."

D30: "Increasing the accuracy of AI-based systems is essential to ensure reliable and safe recommendations."

D31: No comment provided.

D32: "Some personal characteristics, such as genomic factors, can affect the results of AI-based recommendations and should be considered."

D33: "AI could help the healthcare system and improve services by providing timely, evidence-based recommendations."

V. Discussion

The enhancements made to the GAMENet model, particularly the integration of GAT and MHCA, have significantly improved its performance in generating personalized medication recommendations. By leveraging GAT, the model can better capture the complex and non-transitive nature of DDIs, while MHCA ensures a more dynamic and context-aware integration of patient history and drug information. These improvements align with our goal of knowledge translation, where advanced AI models are adapted for real-world applications such as public health kiosks. The modified GAMENet model exemplifies how knowledge of action can be achieved by integrating cutting-edge research into practical healthcare solutions. By embedding this enhanced model into the kiosk system, we aim to bridge the gap between research and routine clinical practice, ensuring that patients receive accurate and safe medication recommendations.

Our experimental results demonstrate the effectiveness of the enhanced GAMENet model. These metrics collectively provide a comprehensive evaluation of the system, balancing accuracy, safety, and clinical relevance. The results, summarized in Table I, indicate that the system, with its enhanced architecture, achieves PRAUC (0.7443) scores compared to the original GAMENet model. These improvements highlight the effectiveness of GAT and MHCA in capturing complex relationships between patient health data, medication history, and DDIs. The system's ability to provide accurate and personalized recommendations is further validated by its low DDI Rate (0.0798), ensuring safer medication suggestions.

Our survey of healthcare professionals reveals both enthusiasm and prudent caution regarding AI-powered drug recommendation systems. While clinicians recognize the technology's potential to enhance efficiency—particularly through workload reduction (90% agreement) and rapid evidence-based recommendations (100% endorsement) in underserved areas—these benefits are tempered by persistent concerns about accuracy thresholds and patient safety. These findings align with emerging literature demonstrating AI's capacity to optimize clinical workflows [84, 85], while also reflecting the healthcare community's appropriate prioritization of patient safety and clinical judgment in technology adoption [86].

The survey uncovered notable variations in acceptance patterns across medical specialties. Pharmacists and General Practitioners (GPs), who work closely with medications and patient care, demonstrated greater confidence in AI's ability to provide effective drug recommendations. In contrast, specialists, particularly those in radiology and psychiatry, showed cautious optimism, valuing AI for its accuracy but insisting on stringent safety protocols. These differences highlight the need for specialty-specific implementation strategies and adaptive AI systems that can accommodate diverse clinical workflows, ensuring that AI enhances, rather than replaces, human expertise [87]. The unanimous clinician preference for AI as a supplementary tool (100% agreement against replacement of pharmacists) reinforces current WHO guidelines advocating for balanced human-AI collaboration in healthcare [87].

Three key requirements emerged for successful clinical integration: First, the overwhelming demand for regulatory oversight (97% support) underscores the need for robust validation frameworks and certification processes. Second, the strong preference for transparent side-effect communication (84.8% favored comprehensive disclosure) suggests that trust-building mechanisms must be central to system design. Third, concerns about algorithmic bias and demographic representation (particularly from providers serving diverse populations) indicate the necessity for continuous monitoring and validation across patient subgroups [88]. These findings collectively inform a roadmap for responsible implementation, emphasizing that technical capabilities must be matched by equally sophisticated safety and oversight mechanisms to achieve clinician acceptance and optimal patient outcomes.

Clinician feedback reveals a multifaceted set of concerns regarding AI-powered medication kiosks that can be categorized into four key areas: (1) System utility and demographic targeting, (2) Safety and reliability, (3) Clinical oversight and medication safety, and (4) Algorithmic bias and equity. These concerns align with established frameworks for responsible AI implementation in healthcare, which emphasize the need for robust validation, human oversight, and equitable performance across populations [89].

To address system utility concerns, we propose developing adaptive interfaces that demonstrate the kiosk's unique value proposition in specific clinical settings (e.g., pharmacies and rural healthcare centers) while exploring hybrid kiosk-mobile architectures. This approach would combine the accessibility of mobile apps with the physical presence of kiosks for functions like secure prescription printing and limited medication dispensing under pharmacist supervision. For safety and

reliability, we recommend implementing multi-layered security protocols, including blockchain-based audit trails, real-time anomaly detection systems, and explainable AI interfaces that provide the transparent rationale for all recommendations. These measures would address both technical vulnerabilities and clinician trust barriers. To mitigate drug safety concerns, we propose integrating real-time pharmacovigilance feeds for updated side-effect data and tiered risk alerts (color-coded by severity), with automated holds on high-risk recommendations.

The clinical oversight concerns necessitate a tiered decision-support system with: (1) Autonomous functionality for low-risk OTC medications, (2) Pharmacist review requirements for moderate-risk recommendations, and (3) Mandatory physician consultation for complex cases. This framework would be complemented by AI guardians that monitor for medication misuse patterns and symptom underreporting. To mitigate algorithmic bias, we propose continuous validation across demographic subgroups using federated learning techniques that maintain privacy while improving model fairness.

In future efforts, the initial phase will involve usability testing with a diverse group of participants representing various demographics, including age groups, ethnic backgrounds, and technological proficiencies. Critical metrics such as recommendation accuracy, user satisfaction (assessed through surveys and interviews), and time spent interacting with the kiosk will be measured. Recommendation accuracy will be evaluated by comparing the kiosk's outputs to clinical guidelines or expert opinions, with a confusion matrix used to identify specific areas where the model may misclassify symptoms or recommend incorrect medications. Additionally, the impact of the kiosk on medication adherence, self-care behaviors, and healthcare utilization will be evaluated through self-reported data and, where feasible, objective data collected in collaboration with healthcare providers.

In the subsequent phase, our proposed automated kiosk will be deployed in high-traffic public areas such as shopping centers, transit hubs, and pharmacies. Data on user interactions, including the frequency of use, types of queries made, and subsequent health outcomes as self-reported by users, will be collected and analyzed. This data will be compared to baseline metrics collected before deployment to quantify the kiosk's contribution to improving public health access and medication adherence. The study will also assess the kiosk's scalability and adaptability in environments with varying network reliability and hardware constraints.

The evaluation process will adhere to strict ethical guidelines, ensuring informed consent, data privacy, and confidentiality. All data collection and analysis procedures will comply with regulations such as GDPR and HIPAA, and participants will be fully informed about the study's objectives and their rights. As part of the Implementation Science framework, we will conduct a rigorous evaluation involving at least 500 participants from diverse demographics. This study will assess the kiosk's impact on healthcare outcomes using metrics such as medication adherence rates, user satisfaction (measured via Likert scales), and the reduction of unnecessary healthcare visits. The findings from this study will provide critical insights into the kiosk's effectiveness and scalability, guiding future iterations and large-scale deployments. By embedding the Kiosk into existing healthcare workflows and continuously monitoring its performance, we aim to ensure that the system is not only effective but also sustainable in diverse clinical and public health environments.

The clinical contributions of the Kiosk system include enhancing medication safety through real-time drug interaction checks, providing personalized OTC medication recommendations, and improving patient access to healthcare in underserved areas. It supports clinical decision-making by offering context-aware recommendations based on patient history. The system also empowers patients to manage minor health conditions independently, potentially reducing unnecessary doctor visits. By integrating advanced AI models, it bridges the gap between research and clinical practice, ensuring safer and more accurate healthcare recommendations.

The clinical applicability and practical utility of the proposed AI-powered kiosk are supported through a combination of acceptable algorithmic performance and expert-based evaluation. Internally, our enhanced model demonstrated modest improvements over baseline architectures in terms of safety, contextual relevance, and overall accuracy of medication recommendations. To assess generalizability, we conducted further validation using the MIMIC-IV dataset, which confirmed that the model maintains consistent performance across diverse and temporally distinct patient populations. These findings support the model's applicability in real-world scenarios and its resilience to data variability.

To complement the technical evaluation, we expanded our expert assessment from 11 to 33 professionals, including pharmacy and clinical experts from various domains. The structured, survey-based evaluation captured perspectives on clinical relevance, safety, usability, scalability, and ethical considerations. Experts affirmed the system's practical utility, particularly emphasizing its value in underserved and high-traffic environments where quick and reliable access to OTC medication guidance is essential. Importantly, respondents viewed the kiosk as a supportive tool that complements—rather than replaces—clinical judgment. The convergence of model-based validation and expert feedback reinforces the kiosk's readiness for deployment as a safe, accessible, and context-aware solution in public health settings.

While this study presents a promising advancement in AI-powered kiosks for OTC medication guidance, several limitations must be acknowledged. First, although performance improvements were observed compared to prior models, the gains across metrics such as Jaccard, F1-Score, and PRAUC were relatively modest and may not yet reach thresholds of clinical significance. Second, despite validation across both MIMIC-III and MIMIC-IV datasets, the model's generalizability beyond these data sources—such as in international healthcare systems or

varied public health environments—remains untested. Third, while expert evaluation was expanded to include 33 pharmacies and clinical professionals, this sample size still limits the statistical power and generalizability of the survey findings. Broader participation across healthcare roles and settings would strengthen external validity. Fourth, this study did not incorporate human-in-the-loop clinical trials or outcome-based validations that directly assess the kiosk's real-world impact on medication adherence, patient safety, or healthcare utilization. Finally, more powerful model architectures, integration with diverse datasets, and end-to-end deployment workflows—including regulatory, ethical, and infrastructure considerations—will be essential in future iterations to achieve both statistically and clinically meaningful impact.

In summary, our future work will employ a three-phase validation approach: 1) First, controlled trials assessing demographic-specific performance; 2) Second, comparative studies of hybrid versus standalone implementations; and 3) Third, longitudinal monitoring of real-world safety outcomes. This comprehensive strategy addresses all raised concerns while aligning WHO guidelines for responsible AI in healthcare [90], ensuring that technological innovation progresses in tandem with patient safety and clinician trust.

VI. Conclusion

The kiosk represents a transformative approach to public health by integrating advanced AI models, such as the enhanced GAMENet architecture with GNNs and MHCA, to deliver accurate and personalized medication recommendations. Experimental results demonstrate improvements in recommendation accuracy, with the system slightly outperforming the original GAMENet model across key metrics. Survey feedback from doctors highlights cautious optimism, emphasizing the system's potential to enhance healthcare access, particularly in remote areas, and its ability to provide real-time drug interaction checks. However, concerns about accuracy, clinical reliability, and the need for human oversight underscore the importance of further refinement. The system prioritizes user privacy through federated learning and promotes inclusivity with multilingual support, accessibility features, and a health education library. By bridging the gap between cutting-edge research and routine clinical practice, the system sets a new standard for personalized healthcare, making advanced medical recommendations accessible to diverse populations. Continued research, real-world deployments, and partnerships with healthcare providers will further enhance their impact, empowering individuals and reducing healthcare disparities.

Code Availability Statement

All code developed for this study is publicly available at: https://github.com/MohammadRSalmanpour/AI-powered-Public-Health-Automated-Kiosk-System-/tree/main

Conflict of Interest

Sonya Falahati, Morteza Alizadeh, Zhino Safahi, Fatemeh Ghazipour, and Mohammad R. Salmanpour are affiliated with TECVOCO CORP. Company, and the remaining authors have no relevant conflicts of interest to disclose.

Author Contributions

Conceptualization, Methodology, Investigation, Resources: SF, MA and MRS; Visualization, Writing and editing—original draft: SF, MA, and ZS; Validation: MRS and NK; Review: MRS, FG, and NK; Supervision and Lead: MRS. All authors had approved the final version.

Acknowledgement

We appreciate the invaluable contributions of our healthcare professionals, including Drs. Ahmad Shariftabrizi, Mehdi Maghsudi, Sara Gharibi, Arman Gorgi, Ali Fathi Jouzdani, Amir Mahmoud Ahmadzadeh, Sajad Amiri, Forough Yousefi, Mohammad Zahedi, Nima Sanati and Shahram Taeb for their support and expertise.

References

[1] T. Bodenheimer and C. Sinsky, "From triple to quadruple aim: Care of the patient requires care of the provider," *The Annals of Family Medicine*, vol. 12, pp. 573–576, 2014.

[2] N. Grace, T. S. Wee, and N. C. Tan, "Health outcomes of patients with chronic disease managed with a healthcare kiosk in primary care: Protocol for a pilot randomized controlled trial," *BMJ Open*, vol. 8, e020265, 2018.

[3] W. Bynum, "Why physicians need to be more than automated medical kiosks," *Acad. Med.*, vol. 89, pp. 212–214, 2014.

[4] Maramba, A. Chatterjee, and C. Newman, "Methods of usability testing in the development of eHealth applications: A scoping review," *Int. J. Med. Inform.*, vol. 126, pp. 95–104, 2019.

[5] S. H. Houser, C. A. Flite, and S. L. Foster, "Privacy and security risk factors related to telehealth services—A systematic review," *Perspectives in Health Information Management*, vol. 20, no. 1, 1f, 2023.

[6] Y. Chan, R. Nagurka, S. Bentley *et al*., "Medical utilization of kiosks in the delivery of patient education: A systematic review," *Health Promot. Perspect.*, vol. 4, pp. 1–8, 2014.

[7] G. Ng, N. Tan, J. Bahadin *et al*., "Development of an automated healthcare kiosk for the management of chronic disease patients in the primary care setting," *J. Med. Syst.*, vol. 40, 169, 2016.

[8] A. Joshi and K. Trout, "Health kiosks as an equal opportunity resource for better health: A systematic review," *Global Health*, pp. 66–70, 2012.

[9] X. Lu, Y. Hao, F. Peng *et al*., "ExpDrug: An explainable drug recommendation model based on space feature mapping," *Neurocomputing*, vol. 619, 129021, 2025.

[10] M. Sharma and S. Mann, "A survey of recommender systems: Approaches and limitations," *Int. J. Innov. Eng. Technol.*, vol. 2, no. 2, pp. 8–14, 2013.

[11] F. Zhu, L. Cui, Y. Xu *et al*., "A survey of personalized medicine recommendation," *Int. J. Crowd Sci.*, vol. 8, no. 2, pp. 77–82, 2024.

[12] R. Jones, "The role of health kiosks in 2009: literature and informant review," *Int. J. Environ. Res. Public Health,* vol. 6, no. 6, pp. 1818–1855, 2009.

[13] D. Nicholas, P. Williams, and P. Huntington, "Health information kiosk use in health organisations: The views of the health professionals," in *Aslib Proc.*, 2001, vol. 53, pp. 368–386.

[14] S. Vilar, C. Friedman, and G. Hripcsak, "Detection of drug-drug interactions through data mining studies using clinical sources, scientific literature and social media," *Brief. Bioinform.*, vol. 19, no. 5, pp. 863–877, 2018.

[15] J. Xu, B. S. Glicksberg, C. Su *et al*., "Federated learning for healthcare informatics," *J. Healthc. Inform. Res.*, vol. 5, pp. 1–19, 2021.
[16] J. Shang, C. Xiao, T. Ma *et al*., "GAMENet: Graph augmented MEmory networks for recommending medication combination," in *Proc. AAAI Conf. Artif. Intell.*, 2019, pp. 1126–1133.
[17] S. Straus, J. Tetroe, and I. Graham, "Defining knowledge translation," *Can. Med. Assoc. J.*, vol. 181, pp. 165–168, 2009.
[18] Y. Zhang, R. Chen, and J. Tang, "LEAP: Learning to prescribe effective and safe treatment combinations for multimorbidity," in *Proc. 23rd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2017, pp. 1315–1324.
[19] S. Saria, A. Butte, and A. Sheikh, "Better medicine through machine learning: What's real, and what's artificial?" *PLoS Med.*, vol. 15, no. 12, e1002721, 2018.
[20] Maramba, R. Jones, D. Austin *et al*., "The role of health kiosks: Scoping review," *JMIR Med. Inform.*, vol. 10, no. 3, e26511, 2022.
[21] Ghebrehiwet, N. Zaki, R. Damseh *et al*., "Revolutionizing personalized medicine with generative AI: A systematic review," *Artif. Intell. Rev.*, vol. 57, 128, 2024.
[22] J. P. Gupta, A. Singh, and R. K. Kumar, "A computer-based disease prediction and medicine recommendation system using machine learning approach," *Int. J. Adv. Res. Eng. Technol.*, vol. 12, no. 3, pp. 673–683, 2021.
[23] M. Letafat-Nejad, P. Ebrahimi, M. Maleki *et al*., "Utilization of integrated health kiosks: A systematic review," *Med. J. Islam. Repub. Iran*, vol. 34, 114, 2020.
[24] E. Oliveira, P. Pacheco, F. Santos *et al*., "The role of kiosks on health services: A systematic review," in *Proc. 11th Int. Conf. Serious Games Appl. Health (SeGAH)*, 2023, pp. 1–6.
[25] R. Miotto, F. Wang, S. Wang *et al*., "Deep learning for healthcare: Review, opportunities and challenges," *Brief. Bioinform.*, vol. 19, no. 6, pp. 1236–1246, 2018.
[26] T. N. T. Tran, A. Felfernig, C. Trattner *et al*., "Recommender systems in the healthcare domain: State-of-the-art and research issues," *J. Intell. Inf. Syst.*, vol. 57, pp. 171–201, 2021.
[27] M. Wensing and R. Grol, "Knowledge translation in health: How implementation science could contribute more," *BMC Med.*, vol. 17, 88, 2019.
[28] S. Bhutani, A. Alian, R. R. Fletcher *et al*., "Vital signs-based healthcare kiosks for screening chronic and infectious diseases: A systematic review," *Communications Medicine,* vol. 5, no. 1, 28, 2025.
[29] C. Lowe and D. Cummin, "The use of kiosk technology in general practice," *J. Telemed. Telecare*, vol. 16, no. 4, pp. 201–203, 2010.
[30] A. C. Smith, E. Thomas, C. L. Snoswell *et al*., "Telehealth for global emergencies: Implications for coronavirus disease 2019 (COVID-19)," *J. Telemed. Telecare*, vol. 26, no. 5, pp. 309–313, 2020.
[31] R. A. Gladia and G. Kavya, "Design and development of non-invasive kiosk for self-care health management," *Research India Publications*, vol. 13, pp. 4787–4794, 2017.
[32] A. Jain, R. Bolle, and S. Pankanti, "Introduction to biometrics," in *Biometrics*, A. K. Jain, R. Bolle, S. Pankanti, eds. New York: Springer, 1996.
[33] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nat. Med.*, vol. 25, pp. 44–56, 2019.
[34] S. Aguirre and A. Rodriguez, "Automation of a business process using Robotic Process Automation (RPA): A case study," in *Proc. Workshop Eng. Appl. (WEA)*, 2017, pp. 65–71.
[35] D. McGraw and K. Mandl, "Privacy protections to encourage use of health-relevant digital data in a learning health system," *NPJ Digit. Med.*, vol. 4, no. 1, 2, 2021.
[36] T. W. Bickmore, L. M. Pfeifer, and B. W. Jack, "Taking the time to care: Empowering low health literacy hospital patients with virtual nurse agents," in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, 2009, pp. 1265–1274.
[37] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial," *JMIR Ment. Health*, vol. 4, no. 2, e7785, 2017.
[38] D. A. Greenwood, P. M. Gee, K. J. Fatkin *et al*., "A systematic review of reviews evaluating technology-enabled diabetes self-management education and support," *J. Diabetes Sci. Technol.*, vol. 11, no. 5, pp. 1015–1027, 2017.
[39] M. R. Salmanpour, A. Gorji, A. F. Jouzdani *et al*., "Exploring several novel strategies to enhance prediction of lung cancer survival time," in *Proc. IEEE Nucl. Sci. Symp. (NSS), Med. Imag. Conf. (MIC), Room Temp. Semicond. Detect. Conf. (RTSD)*, 2024, pp. 1–2.
[40] M. R. Salmanpour, M. Hosseinzadeh, E. Modiri *et al*., "Advanced survival prediction in head and neck cancer using hybrid machine learning systems and radiomics features," in *Proc. SPIE Med. Imag.*, 2022, vol. 12036, pp. 314–321.
[41] M. Salmanpour, M. Shamsaei, A. Saberi *et al*., "Hybrid machine learning methods for robust identification of Parkinson's disease subtypes," *J. Nucl. Med.*, vol. 61, no. 2, 2020.
[42] M. R. Salmanpour, S. M. Rezaeijo, M. Hosseinzadeh *et al*., "Deep versus handcrafted tensor radiomics features: Prediction of survival in head and neck cancer using machine learning and fusion techniques," *Diagnostics*, vol. 13, no. 10, 1696, 2023.
[43] A. Javanmardi, M. Hosseinzadeh, G. Hajianfar *et al*., "Multi-modality fusion coupled with deep learning for improved outcome prediction in head and neck cancer," in *Proc. SPIE Med. Imag.*, 2022, vol. 12032, pp. 664–668.
[44] M. R. Salmanpour, A. Mousavi, Y. Xu *et al*., "Do high-performance image-to-image translation networks enable the discovery of radiomic features? Application to MRI synthesis from ultrasound in prostate cancer," in *Proc. Int. Workshop Adv. Simplifying Med. Ultrasound*, 2024, pp. 24–34.
[45] S. Kalayinia, G. Hajianfar, T. Talebi *et al*., "Prediction of Parkinson's disease pathogenic variants via semi-supervised hybrid machine learning systems, clinical information and radiomics features," *J. Nucl. Med.*, vol. 64, 1154, 2023.
[46] G. Hajianfar, S. Kalayinia, M. Hosseinzadeh *et al*., "Prediction of Parkinson's disease pathogenic variants using hybrid machine learning systems and radiomic features," *Phys. Med.*, vol. 113, 102647, 2023.
[47] R. Van Meteren and M. Van Someren, "Using content-based filtering for recommendation," in *Proc. Mach. Learn. New Inf. Age: MLnet/ECML2000 Workshop*, 2000, vol. 30, pp. 47–56.
[48] J. B. Schafer, D. Frankowski, J. Herlocker *et al*., "Collaborative filtering recommender systems," in *The Adaptive Web: Methods and Strategies of Web Personalization*, P. Brusilovsky, A. Kobsa, W. Nejdl, eds. Springer Berlin Heidelberg, 2007, pp. 291–324.
[49] P. B. Thorat, R. M. Goudar, S. Barve, "Survey on collaborative filtering, content-based filtering and hybrid recommendation system," *Int. J. Comput. Appl.*, vol. 110, no. 4, 2015.
[50] M. R. Salmanpour, M. Hosseinzadeh, M. Bakhtiari *et al*., "Drug amount prediction in Parkinson's disease using hybrid machine learning systems and radiomics features," *J. Nucl. Med.*, vol. 63, 2256, 2022.
[51] M. J. Pazzani, "A framework for collaborative, content-based and demographic filtering," *Artif. Intell. Rev.*, vol. 13, pp. 393–408, 1999.
[52] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, 2009.
[53] T. Shahid, S. Singh, S. Gupta *et al*., "Analyzing patient reviews for recommending treatment using NLP and deep learning-based approaches," in *Proc. Int. Conf. Adv. Interdiscip. Res.*, 2022, pp. 179–190.
[54] E. Choi, M. T. Bahadori, J. Sun *et al*., "RETAIN: An interpretable predictive model for healthcare using reverse time attention mechanism," in *Proc. 30th Int. Conf. Neural Inf. Process. Syst.*, 2016, pp. 3512–3520.
[55] Y. An, L. Zhang, H. Yang *et al*., "Prediction of treatment medicines with dual adaptive sequential networks," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 11, pp. 5496–5509, 2022.
[56] Z. Zheng, C. Wang, T. Xu *et al*., "Drug package recommendation via interaction-aware graph induction," in *Proc. Web Conf.*, 2021, 1284–1295.
[57] Q. Teng, Z. Liu, Y. Song *et al*., "A survey on the interpretability of deep learning in medical diagnosis," *Multimedia Syst.*, vol. 28, pp. 2335–2355, 2022.
[58] M. R. Salmanpour, A. Mousavi, Y. Xu *et al*. "Influence of high-performance image-to-image translation networks on clinical visual assessment and outcome prediction: Utilizing ultrasound to MRI translation in prostate cancer," arXiv Preprint, arXiv:2501.18109, 2025.

[59] S. M. Rezaeijo, A. Mahboubisarighieh, S. J. Nesheli *et al*., "Use of deep image-to-image translations to assess complementary value of imaging modalities: Application to PET and CT images in head and neck cancer," *J. Nucl. Med.*, vol. 64, P1585, 2023.
[60] M. R. Salmanpour, M. Hosseinzadeh, M. Bakhtiyari *et al*., "Prediction of drug amount in Parkinson's disease using hybrid machine learning systems and radiomics features," *Int. J. Imaging Syst. Technol.*, vol. 33, no. 4, pp. 1437–1449, 2023.
[61] W. Yue, M. Wang, L. Zhang *et al*., "A-GSTCN: An augmented graph structural-temporal convolution network for medication recommendation based on electronic health records," *Bioengineering*, vol. 10, no. 11, 1241, 2023.
[62] Y. Ren, Y. Shi, K. Zhang *et al*., "A drug recommendation model based on message propagation and DDI gating mechanism," *IEEE J. Biomed. Health Inform.*, vol. 26, no. 7, pp. 3478–3485, 2022.
[63] W. Y. Tan, Q. Gao, R. W. Oei *et al*., "Diabetes medication recommendation system using patient similarity analytics," *Sci. Rep.*, vol. 12, 20910, 2022.
[64] D. Pinto, P. Costa, R. Camacho *et al*., "Predicting drugs adverse side-effects using a recommender-system," in *Proc. 18th Int. Conf. Discov. Sci.*, Banff, 2015, pp. 201–208.
[65] P. Symeonidis, S. Chairistanidis, and M. Zanker, "Safe, effective and explainable drug recommendation based on medical data integration," *User Model. User-Adapt. Interact.*, vol. 32, pp. 999–1018, 2022.
[66] V. Beretta, "Knowledge transfer and exchange in healthcare: A literature review," in *Development and Implementation of Health Technology Assessment*, New York: Springer, 2021, pp. 11–52.
[67] I. D. Graham, J. Logan, M. B. Harrison *et al*., "Lost in knowledge translation: Time for a map?" *J. Contin. Educ. Health Prof.*, vol. 26, no. 1, pp. 13–24, 2006.
[68] F. Jiang, Y. Jiang, and H. Zhi, "Artificial intelligence in healthcare: Past, present and future," *Stroke Vasc. Neurol.*, vol. 2, no. 4, 2017.
[69] T. Greenhalgh, G. Robert, F. Macfarlane *et al*., "Diffusion of innovations in service organizations: Systematic review and recommendations," *Milbank Q.*, vol. 82, no. 4, pp. 581–629, 2004.
[70] J. M. Grimshaw, M. P. Eccles, J. N. Lavis *et al*., "Knowledge translation of research findings," *Implement. Sci.*, vol. 7, 50, 2012.
[71] M. R. Salmanpour, S. Amiri, S. Gharibi *et al*., "Radiological and biological dictionary of radiomics features: Addressing understandable AI issues in personalized prostate cancer, dictionary version PM1.0," *J. Digit. Imaging Inform. Med.*, pp. 1–22, 2025.
[72] S. S. Mehrnia, Z. Safahi, A. Mousavi *et al*., "Landscape of 2D deep learning segmentation networks applied to CT scan from lung cancer patients: A systematic review," *J. Imaging Inform. Med.*, pp. 1–30, 2025.
[73] F. Gama, D. Tyskbo, J. Nygren, *et al*., "Implementation frameworks for artificial intelligence translation into health care practice: Scoping review," *J. Med. Internet Res.*, vol. 24, no. 1, e32215, 2022.
[74] M. R. Salmanpour, A. Gorji, A. Mousavi *et al*., "Enhanced lung cancer survival prediction using semi-supervised pseudo-labeling and learning from diverse PET/CT datasets," *Cancers*, vol. 17, no. 2, 285, 2024.
[75] J. Kröplin, L. Maier, J. H. Lenz *et al*., "Knowledge transfer and networking upon implementation of a transdisciplinary digital health curriculum in a unique digital health training culture: Prospective analysis," *JMIR Med. Educ.*, vol. 10, e51389, 2024.
[76] A. E. W. Johnson, T. J. Pollard, L. Shen *et al*., "MIMIC-III, a freely accessible critical care database," *Sci. Data*, vol. 3, pp. 1–9, 2016.
[77] N. P. Tatonetti, P. P. Ye, R. Daneshjou *et al*., "Data-driven prediction of drug effects and interactions," *Sci. Transl. Med.*, vol. 4, no. 125, 125ra31, 2012.
[78] A. E. W. Johnson, L. Bulgarelli, L. Shen *et al*., "MIMIC-IV, a freely accessible electronic health record dataset," *Sci. Data*, vol. 10, no. 1, 1, 2023.
[79] S. Falahati, F. Zamani, M. A. Khodamoradib *et al*., "Predicting drug-target affinity by discovering pairwise interactions using cross attention network," *Int. J. Eng.*, vol. 38, no. 8, pp. 1737–1748, 2025.
[80] G. M. Silverman, H. S. Sahoo, N. E. Ingraham *et al*., "NLP methods for extraction of symptoms from unstructured data for use in prognostic COVID-19 analytic models," *J. Artif. Intell. Res.*, vol. 72, pp. 429–474, 2021.
[81] C. Dreisbach, T. A. Koleck, P. E. Bourne *et al*., "A systematic review of natural language processing and text mining of symptoms from electronic patient-authored text data," *Int. J. Med. Inform.*, vol. 125, pp. 37–46, 2019.
[82] T. A. Koleck, C. Dreisbach, P. E. Bourne *et al*., "Natural language processing of symptoms documented in free-text narratives of electronic health records: A systematic review," *J. Am. Med. Inform. Assoc.*, vol. 26, no. 4, pp. 364–379, 2019.
[83] M. R. Salmanpour, M. Alizadeh, G. Mousavi *et al*., "Machine learning evaluation metric discrepancies across programming languages and their components in medical imaging domains: Need for standardization," *IEEE Access*, vol. 13, pp. 47217–47229, 2025.
[84] P. Keikhosrokiani, K. Balasubramaniam, M. Isomursu *et al*., "Drug recommendation system for healthcare professionals' decision-making using opinion mining and machine learning," in *Proc. Nord. Conf. Digit. Health Wireless Solut.*, 2024, pp. 222–241.
[85] P. Fu, "Transforming clinical workflows with Artificial Intelligence (AI)-based technologies," in *Reengineering Clinical Workflow in the Digital and AI Era: Toward Safer and More Efficient Care*, K. Zheng, J. Westbrook, V. L. Patel, eds. New York: Springer, 2025, pp. 35–55.
[86] N. N. Botha, C. E. Segbedzi, V. K. Dumahasi *et al*., "Artificial intelligence in healthcare: A scoping review of perceived threats to patient rights and safety," *Arch. Public Health*, vol. 82, 188, 2024.
[87] H. Shamszare and A. Choudhury, "Clinicians' perceptions of artificial intelligence: Focus on workload, risk, trust, clinical decision making, and clinical integration," *Healthcare*, vol. 11, no. 16, 2308, 2023.
[88] I. Loukili, N. S. Goedhart, and T. Zuiderent-Jerak *et al*., "Digitalizing access to care: How self-check-in kiosks shape access to care and efficiency of hospital services," *Media Commun.*, vol. 12, 2024.
[89] K. Archana, "Responsible AI Implementation in Healthcare Organizations," in *Responsible AI for Digital Health and Medical Analytics*, 2025, pp. 1–14.
[90] N. Naik, B. M. Hameed, D. K. Shetty *et al*., "Legal and ethical consideration in artificial intelligence in healthcare: Who takes responsibility?" *Front. Surg.*, vol. 9, 862322, 2022.