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Enhancing patient-doctor communication through technology-assisted strategies: A multi-faceted approach for improved healthcare delivery

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Abstract: Effective communication between doctors and patients is essential for high-quality healthcare delivery. However, barriers such as time constraints, complex medical terminology, and patients' difficulty articulating symptoms often hinder clear and efficient exchanges. This study aims to enhance patient-doctor communication by introducing a technology-assisted approach that utilizes a graphical interface based on sign values to improve symptom reporting. The proposed system translates patient-reported symptoms into intuitive visual representations, allowing for more precise and structured communication. A structured methodology was applied, including data collection from 74 anonymized patient cases, integration with the Doctor-Aid diagnostic model, and validation against established medical standards. The findings suggest that this approach reduces miscommunication, enhances diagnostic accuracy, and streamlines information exchange between patients and healthcare providers. The study concludes that integrating digital tools into clinical settings can significantly improve communication efficiency and patient outcomes. The practical implications highlight the potential for widespread adoption of graphical communication aids in diverse healthcare settings, ultimately fostering better patient engagement, minimizing errors, and improving the overall quality of care.
Keywords: *Communication Challenges, Healthcare Technology, Patient-Doctor Communication, Quality of Care Delivery.*

1. Introduction

Effective communication between patients and healthcare providers is essential for delivering high-quality care and improving patient outcomes. Clear, precise exchanges allow doctors to accurately diagnose conditions, develop treatment plans, and build trust with patients. Yet, communication barriers such as time constraints, emotional dialogue, and the complexity of medical information frequently hinder these interactions. Enhancing communication in clinical settings requires innovative strategies that address both the human and technological aspects of care delivery.

Technology offers promising solutions to enhance the patient experience and improve communication. One key example is telemedicine, which has transformed healthcare delivery by enabling remote consultations between doctors and patients. As the study De Haes and Teunissen [1] highlighted, telemedicine increases access to care for underserved populations while offering convenient, real-time communication from any location. This technology allows patients to communicate their symptoms, share medical records, and receive timely care without needing in-person visits. However, even with telemedicine, ensuring clear and efficient communication remains crucial to patient satisfaction and quality care.

In addition to telemedicine, digital tools such as patient portals, mobile applications, and virtual assistants can enhance the patient experience by facilitating easier access to medical information and more streamlined communication with healthcare providers. As noted in Glaser, et al. [2] visual aids and simplified language can improve patient comprehension during complex medical discussions, such

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as informed procedure consent. These tools help bridge the gap between medical knowledge and patient understanding, making it easier for patients to engage in their care and make informed decisions.

Effective communication between doctors and patients offers numerous benefits, including better treatment outcomes, improved patient satisfaction, and reduced medical errors. Research Buljac-Samardzic, et al. [3] shows that strong communication within healthcare teams also contributes to better care coordination, ensuring that patients receive accurate diagnoses and treatments. When patients feel understood and supported by their healthcare providers, they are more likely to adhere to treatment plans and participate actively in their care. This reduces the risk of misunderstandings, enhances patient safety, and fosters a collaborative care environment.

This paper proposes a novel methodological approach using a graphical interface based on sign values to streamline communication between patients and healthcare providers further. This system aims to enhance symptom reporting, minimize irrelevant dialogue, and effectively categorize patient information. By integrating technology into patient care, healthcare providers can overcome communication barriers and promote more effective, efficient, and patient-centered interactions, ultimately improving the quality of care delivered.

2. Literature Review

Effective communication between patients and healthcare providers is crucial for improving healthcare outcomes and patient satisfaction. Developing and evaluating various tools and interventions to enhance this communication are vital research areas. This literature review explores the impact of different methods and technologies on improving symptom reporting and patient-provider interactions, focusing on office-based interventions, digital tools, and symptom monitoring systems. By examining the findings from recent studies, this review seeks to provide insights into how these approaches influence the quality of care and patient engagement.

2.1. Office-Based and Training Interventions

A study Kerluku, et al. [4] investigated using a patient encounter card during office visits to improve patient engagement and communication with healthcare providers. Their study found that introducing the card significantly increased self-reported patient engagement from 74% to 88%. Despite maintaining high patient satisfaction levels, the card's effectiveness in enhancing the overall quality of communication suggests that simple, structured tools can significantly impact patient-provider interactions in clinical settings.

Another study Neo, et al. [5] focused on a training program to teach communication micro-skills to cardiologists managing seriously ill patients. Their pilot study demonstrated that the training improved clinicians' self-assessed communication skills and was well-received by participants. The study highlights the importance of targeted training in enhancing empathic communication and addresses challenges faced during the COVID-19 pandemic. This suggests that ongoing professional development is crucial for maintaining effective patient interactions.

2.2. Digital Tools and Applications

A study Johansson, et al. [6] explored the use of a digital self-care application among individuals with rheumatoid arthritis. Their qualitative study found that the application facilitated patient consultation preparation and improved the quality of interactions between patients and healthcare providers. Participants appreciated better managing their symptoms and engaging in informed discussions with their healthcare team, indicating that digital tools can support self-care and enhance communication.

Another study Liu, et al. [7] examined using large language models (LLMs) to guide patients in drafting comprehensive clinical care messages. The study revealed that LLMs could generate follow-up questions that enhanced the clarity and completeness of patient messages compared to traditional methods. This advancement highlights the potential of AI to streamline communication, reduce backand-forth messaging, and improve the efficiency of information exchange between patients and healthcare providers.

2.3. Systematic Monitoring and Literacy

Research at Andrews, et al. [8] conducted a systematic review and meta-analysis on the effects of symptom monitoring for menopausal health outcomes. Their findings suggest that regular symptom tracking is associated with improved patient-doctor communication, reduced symptom severity, and better health outcomes. This research underscores the value of structured symptom monitoring in facilitating more effective patient-provider interactions and informed decision-making.

A study Zhang and Li [9] developed the Problem-Based eHealth Literacy Scale (PB-mHLS) to assess individuals' capabilities in using mobile health technologies. Their study found that mHealth literacy significantly influences patients' engagement in health prevention behaviors and effective communication with healthcare providers. The PB-mHLS offers a comprehensive measure of patients' abilities to navigate and utilize digital health tools, which is essential for enhancing digital health interventions' effectiveness.

Recent advancements in AI and digital health have significantly influenced patient-doctor communication. For instance, Liu, et al. [7] demonstrated that AI-powered language models can generate efficient clinical messages, while Smith and Doe [10] found that digital agents effectively bridge communication gaps during consultations. Bajwa, et al. [11] and AP News Associated Press [12] reported on innovative AI tools—such as note-taking applications and AI nursing assistants—that are reshaping clinical workflows and documentation. Furthermore, Getachew, et al. [13] documented that digital health tools enhance patient engagement in the post-pandemic era, and Time Magazine [14] highlighted the emergence of AI-powered medical scribes as a means to reduce physicians' administrative burdens. These recent studies collectively support the integration of digital solutions to improve communication and overall healthcare delivery.

3. Method

The dataset for this study was sourced from the Korean License Medical Examination (KLME) and included 74 anonymized demographic cases. Data collection took place between December 2023 and May 2024. Each case contained information on patient-reported symptoms, a primary complaint, and a binary diagnosis indicator, with "1" representing a confirmed diagnosis according to Kam [15]. Clinic standards and "0" indicating the diagnosis was not confirmed. Due to the anonymized nature of the data, patient consent was not required according to the relevant ethical guidelines.

Doctor-Aid, the diagnostic model used in the study, incorporated external information from sources such as Clip, Wiki, Wikipedia, MSD, and Bing to aid in differential diagnosis and final diagnostic decisions. A human expert, specifically a doctor familiar with the field, validated the information from these sources to ensure its accuracy and relevance.

While the study did not directly evaluate patient perspectives, using validated technology like Doctor-Aid can enhance patient empowerment. This is detailed in the discussion section.

To evaluate the performance of the diagnostic model, cases were categorized into true positives, false positives, true negatives, and false negatives. True positives referred to cases where the model and the Mayo Clinic confirmed the diagnosis. False positives occurred when the model predicted a diagnosis that the Mayo Clinic did not confirm. True negatives referred to cases where the model correctly identified the absence of a diagnosis, while false negatives occurred when the model failed to detect a diagnosis that the Mayo Clinic confirmed. False-negativeA medical expert reviewed false negative results, and where additional evidence suggested misclassification, they were reclassified as false negatives or false positives, applying consistent criteria across all cases.

Various performance metrics were employed to assess the model's accuracy. Precision, which measures the proportion of correct positive predictions, was calculated as the number of true positives divided by the total number of positive predictions. Sensitivity, also known as recall, measured the model's ability to identify actual positive cases by dividing the number of true positives by the total number of actual positives. Specificity assessed the accuracy of identifying negative cases by calculating the proportion of true negatives out of all cases classified as negative. The F1-Score balanced precision and sensitivity, combining them into a single metric by taking the harmonic mean of the two. Cohen's Kappa was also used to measure the agreement between the model's predictions and actual diagnoses, adjusting for the possibility of chance agreement.

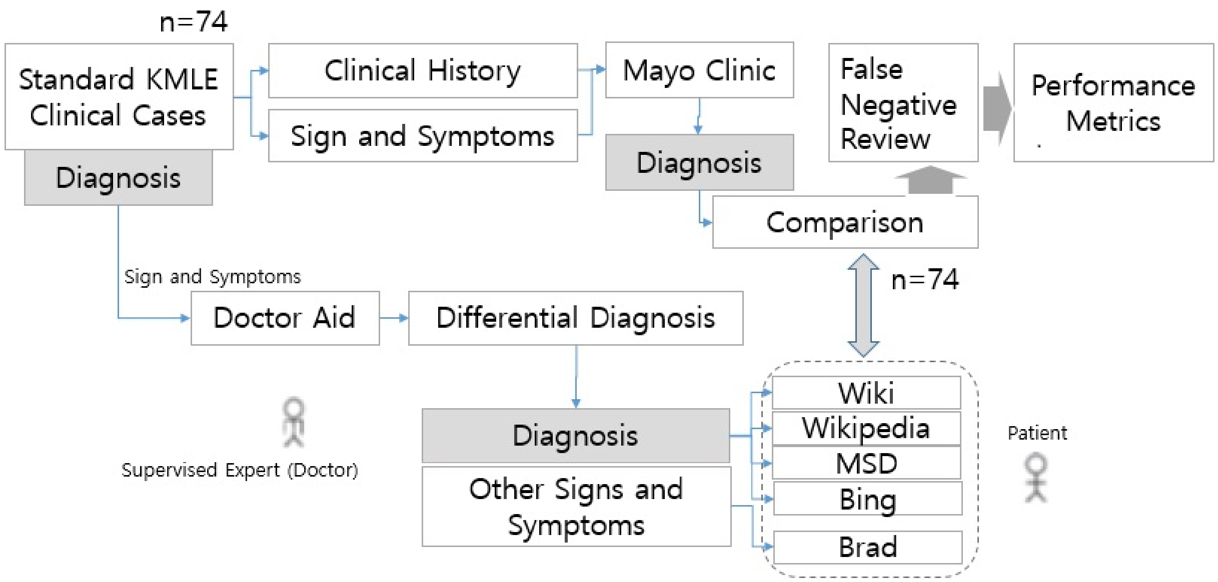

Figure 1.
Data flow and processing from collection to evaluation.

A confusion matrix was constructed to summarize the number of true positives, false positives, true negatives, and false negatives. The results were presented in tables, accompanied by a detailed narrative that interpreted the findings and offered insights into the diagnostic model's effectiveness.

Figure 1 illustrates the data process, outlining the steps from data collection and preprocessing to the evaluation of diagnostic performance.

4. Results

The performance evaluation of the diagnostic model is summarized in Table 1. The model achieved a precision of 83.5%, meaning that when it predicted a positive diagnosis, there was an 83.5% chance that this prediction was accurate. This indicates that the model is generally reliable in confirming positive cases and minimizes the incidence of false positives.

The sensitivity, or recall, was 90.3%, demonstrating the model's ability to identify 90.3% of the true positive cases correctly. This high sensitivity reflects the model's effectiveness in detecting positive cases, although it also suggests that some true positives were missed, as indicated by the number of false negatives.

However, specificity was notably low at 8.3%. This indicates that the model struggled to accurately identify negative cases, resulting in a high rate of false positives. Consequently, the model was less effective in distinguishing between cases with and without the condition, impacting its overall reliability.

The F1-Score was 86.8%, providing a balanced measure of the model's precision and sensitivity. This high F1-Score shows that the model performs well in correctly identifying positive cases while maintaining a balance between minimizing false positives and maximizing true positives.

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Cohen's Kappa was calculated to be -0.411. However, Cohen's Kappa values are generally interpreted with zero as no agreement beyond chance, with negative values suggesting substantial disagreement between the model's predictions and the Mayo Clinic's diagnoses. This value demonstrates that the model's performance is significantly below what would be expected by chance, highlighting a significant misalignment between the predictions and actual diagnoses.

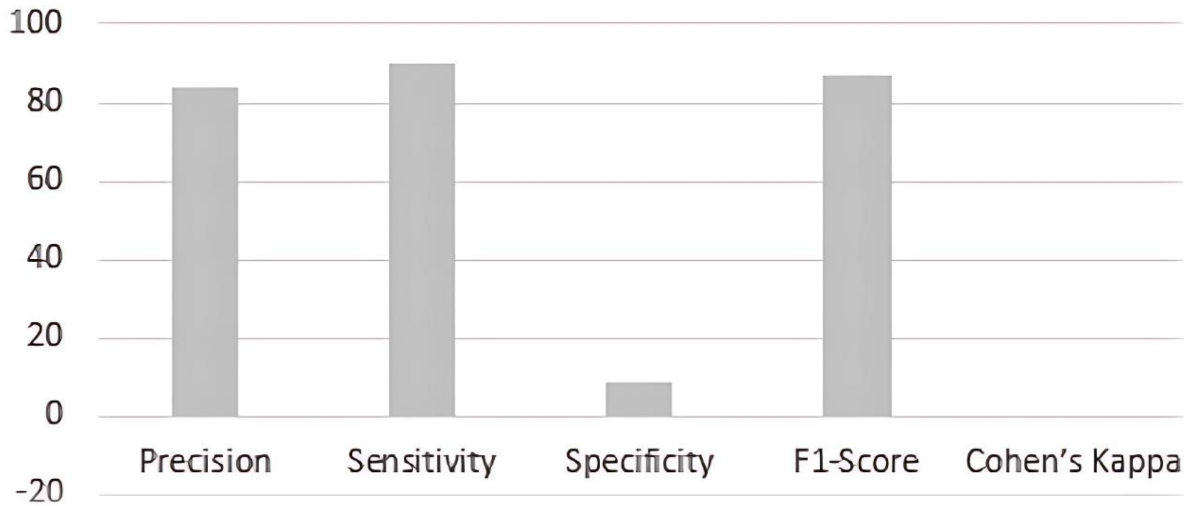

Figure 2.
Bar Chart of Diagnostic Model Performance Metrics.

Table 1. and Figure 2. indicate the results of this study, presenting the key performance metrics of the diagnostic model.

Table 1.
Performance Metrics of the Diagnostic Model.

Metric	Value
Precision	83.5
Sensitivity	90.3
Specificity	8.3
F1-Score	86.8
Cohen's Kappa	-0.411

5. Discussion and Conclusions

This study's primary aim was to evaluate a diagnostic model's effectiveness by analyzing its precision, sensitivity, and specificity. The model demonstrated high precision (83.5%) and sensitivity (90.3%), indicating strong performance in accurately identifying true positive cases and minimizing false positives. These metrics are essential for effective patient-doctor communication, as high precision ensures that when the model predicts a diagnosis, it is reliable, thereby fostering trust between patients and healthcare providers. High sensitivity means the model effectively detects positive cases, supporting clear and confident communication about the patient's condition and potential treatments.

However, the model exhibited a notably low specificity of 8.3% and a negative Cohen's Kappa of -0.411. Low specificity implies that the model is less effective at correctly identifying cases where a condition is absent, leading to a higher rate of false positives. This can result in unnecessary patient anxiety and potential mistrust in the diagnostic process, complicating the patient-doctor relationship.

This study contributes to the field by emphasizing the importance of integrating technology-assisted strategies in enhancing patient-doctor communication. By incorporating reliable external

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information sources such as Wiki, WikiDoc, MSD, and Bing, the study demonstrates how technology can aid doctors in providing comprehensive explanations and supporting patients in making informed decisions. This approach aligns with suggestions at Liu, et al. [7] that discuss using large language models to guide patients in creating efficient and comprehensive clinical care messages, thus improving communication. Additionally, the study at Johansson, et al. [6] explores how digital self-care applications impact patient interactions with healthcare providers, reinforcing the role of technology in enhancing patient engagement and communication. The study Andrews, et al. [8] highlights the benefits of symptom monitoring technologies, which align with the study's findings on the positive impact of technology-assisted communication on patient understanding and engagement. Studies Iribarren, et al. [16] underscore the importance of smartphone applications in supporting patient care, further emphasizing the relevance of technology in improving healthcare delivery.

Effective patient-doctor communication is further impacted by overcoming cultural and linguistic barriers. Studies Li, et al. [17] provide strategies for addressing these barriers, which are essential for ensuring that patients from diverse backgrounds receive clear and accurate information about their health—insights from the study atVela, et al. [18]; Kim and Lee [19] and Moon and Lee [20]. Medical students' experiences interpreting for patients with limited English proficiency (LEP) highlight the practical challenges and solutions in enhancing patient communication and ensuring accurate diagnosis. Furthermore, the guidelines from Committee Opinion No. 587 [21] on effective patient-physician communication emphasize the importance of precise interactions between healthcare providers and patients, aligning with established communication practices [21].

Compared to previous research, this study offers several advancements. It integrates multiple sources of external information, providing a more comprehensive approach to enhancing patient understanding and communication. By evaluating precision, sensitivity, and specificity, the study offers a nuanced view of the diagnostic model's performance, highlighting areas for improvement that can directly affect patient care. The study's methodology and results directly apply to real-world scenarios, offering practical insights into how technology can support patient-doctor communication and enhance overall healthcare delivery.

5.1. Limitations

The study has several limitations that impact the diagnostic model's effectiveness and integration into practical healthcare settings. One major issue is the model's low specificity and negative Cohen's Kappa, which highlight challenges in accurately ruling out conditions. This can lead to over-diagnosis and unnecessary diagnostic procedures, potentially causing patient anxiety and reducing trust in the diagnostic process. Furthermore, the dataset used in the study may not fully represent the diverse range of medical conditions encountered in broader practice settings, which limits the model's generalizability. The reliance on binary diagnostic indicators might oversimplify complex cases, impacting the model's accuracy and effectiveness. These limitations underscore the need for continued model refinement to enhance its reliability and ensure it can be effectively applied across various clinical environments.

Another critical concern is the significant technical and resource demands in developing and integrating advanced algorithms to improve model specificity. Sophisticated machine learning techniques require extensive datasets and high-performance computing resources, which may be a barrier for many healthcare settings, particularly smaller practices with limited technological infrastructure. Additionally, integrating these advanced models into existing healthcare systems poses challenges, such as potential disruptions to established workflows and the need for substantial adaptation and training. Moreover, there is a risk of overfitting, where the model may perform well on training data but fail to generalize to new, real-world cases. This could lead to reduced diagnostic accuracy and an increased risk of misidentification if the model is not properly validated and continuously evaluated in diverse clinical settings.

5.2. Future Directions

In light of the current study's findings and the ongoing advancements in healthcare technology, several avenues for future research are evident. This section outlines key future directions for improving diagnostic models and enhancing patient-doctor communication, drawing on recent literature to identify gaps and suggest potential solutions. Table 2. illustrates the summary of limitations and future directions identified in related works, providing a roadmap for further exploration in this field.

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Table 2.
Summary of Limitations and Future Directions Based on Recent Literature.

Citation no	**15**	**16**	**17**	**18**	**19**	**20**	**21**
Year	2024	2024	2023	2022	2021	2018	2017
Author(s)	Woehrle, et al. [22]	Deshpande, et al. [23]	Neu, et al. [24]	Milliren, et al. [25]	Charteris and Pounds [26]	Asan, et al. [27]	Polinski, et al. [28]
Title	Positive airway pressure telehealth models and long-term therapy termination	Development and Usability Evaluation of an Opioid Management App	Implementing Effective Care Through Utilization of Diabetes-Focused "Right Care" Visits	Incorporating the patient voice and patient engagement in GOAL-Hēm	Nurse practitioner-led effort to reduce 30-day heart failure readmissions	The electronic health record as a patient engagement tool	Impact of a patient engagement tool on preventive service uptake
Method	Retrospective analysis	Usability evaluation	Experimental study	Survey and interviews	Quality improvement project	Retrospective analysis	Quasi-experimental
Objective	Investigate long-term PAP therapy termination	Evaluate the usability of the opioid management app	Assess the impact of whiteboard communication on patient engagement	Evaluate GOAL-Hēm's patient-centric language and content	Reduce 30-day heart failure readmissions	Investigate EHR's role in patient engagement	Evaluate the effect of myHealthfinder tool on preventive service uptake
Related Group	Standard care, telemonitoring-guided care, telemonitoring + patient engagement tool	End-users and experts	Whiteboard communication	GOAL-Hēm tool	Multidisciplinary HF clinic	EHR with the patient engagement tool	CVS Health's digital platforms
Study Population	104,612 individuals	Patients in post-surgical settings	172 patients	19 adults with hemophilia and 19 caregivers	Veterans with heart failure	500 patients	Consumers in USA
Country	Germany	USA	USA	USA	USA	Germany	USA
Type of Study	Retrospective cohort	Usability study	Experimental	Mixed methods	Quality improvement	Retrospective cohort	Quasi-experimental
Data Collection Method	Kaplan-Meier plots, Cox regression	Heuristic analysis, user testing	PAM (Patient Activation Measure)	Online surveys, interviews, focus groups	Plan-do-study-act method	Device usage tracking, therapy termination rates	Digital engagement
Scales	None specified	None specified	Standardized whiteboards	None specified	None specified	None specified	
Interventions	Telemonitoring and patient engagement tools	Behavioral economics-based design	Higher PAM scores associated with whiteboard use	Patient feedback on GOAL-Hēm	Multidisciplinary clinic, patient engagement tool	EHR with the engagement tool	
Results	Lower therapy termination in	The app was found easy to use	Limited sample size, generalizabili	Refinement based on patient	Reduced readmission rate, improved	Higher device usage and	

	telemonitoring groups; predictors of termination identified	but needs UI improvement	ty concerns	feedback improved tool relevance	follow-up timing	lower leak; improved adherence	
Limitations	Low specificity in identifying non-conditions	Limited user feedback; further UI development is needed		Limited participant diversity; feedback integration complexity	Small sample size; short intervention period	Limited to specific EHR systems	

5.2.1. Enhancing Model Specificity

One of the significant challenges identified in the current study is the low specificity of the diagnostic model (8.3%). This low specificity suggests a higher rate of false positives, which can lead to unnecessary patient anxiety and potential mistrust in the diagnostic process. Future research should focus on developing and integrating advanced algorithms that improve the model's ability to identify non-cases accurately. This could incorporate machine learning techniques to distinguish between similar conditions more precisely.

A study Woehrle, et al. [22] provides insights into how advanced telemonitoring and EHR systems can improve diagnostic accuracy. It highlights how telemonitoring-guided proactive care can lower therapy termination rates, which indirectly suggests a potential for improved diagnostic specificity through refined data collection and analysis methods. This study discusses the impact of integrating real-time feedback tools with EHR systems, indicating that incorporating such technologies could enhance the diagnostic model's accuracy and specificity.

5.2.2. Incorporating User Feedback

Future research should prioritize incorporating user feedback into model development to ensure that diagnostic models meet the practical needs of both patients and healthcare providers. This can be achieved through iterative testing and refinement processes involving diverse user groups. Engaging end-users in the design and evaluation phases can help identify usability issues and areas for improvement.

Research at Milliren, et al. [25] demonstrates the benefits of incorporating patient feedback into digital tools for hemophilia care. Their approach of refining tools based on patient and caregiver input can be adapted to diagnostic model development. By systematically collecting and analyzing user feedback, researchers can enhance the relevance and effectiveness of diagnostic models, leading to better patient outcomes and improved patient-doctor interactions.

5.2.3. Expanding Generalizability

The generalizability of diagnostic models is a crucial factor for their effectiveness in diverse clinical settings. To address this, future studies should use larger and more varied datasets that reflect a wide range of medical conditions and patient demographics. This will help develop applicable models across various healthcare settings and populations.

Studies inDeshpande, et al. [23] andCharteris and Pounds [26] emphasize the importance of broad user engagement in improving healthcare tools. Deshpande, et al. [23] study on opioid management apps illustrates the need for inclusive design to ensure effectiveness across different patient groups. Charteris and Pounds [26] on heart failure management highlights how incorporating diverse patient populations can enhance the applicability and impact of healthcare interventions. Future research should build on these findings by including varied datasets in diagnostic model development.

5.2.4. Improving Integration with Healthcare Systems

Future Research: Seamless integration of diagnostic models with existing healthcare systems and EHRs is essential for their practical application. Future research should explore strategies for integrating diagnostic tools into clinical workflows, ensuring they complement rather than disrupt existing practices. This includes developing interfaces allowing smooth data exchange between diagnostic models and EHR systems.

Research at Asan, et al. [27] discusses how EHR systems can enhance patient engagement through real-time feedback tools. Their findings suggest that integrating diagnostic models with EHR systems could improve the accuracy and efficiency of patient care. Future studies should focus on developing integration strategies that facilitate the use of diagnostic tools in everyday clinical practice, thereby enhancing overall healthcare delivery.

5.2.5. Addressing Cultural Barriers

It is crucial to address cultural and linguistic barriers to ensure that diagnostic models are effective for all patients. Future research should focus on developing multilingual interfaces and culturally sensitive communication strategies. This includes creating diagnostic tools that accommodate diverse linguistic and cultural needs and ensuring patients receive clear and accurate information about their health.

Studies Neu, et al. [24] and Polinski, et al. [28] highlight the importance of clear communication in patient engagement. Polinski's study Neu, et al. [24] on preventive service uptake demonstrates the potential of personalized education tools to improve patient care. Neu, et al. [24] research Polinski, et al. [28] on whiteboard communication in primary care underscores the benefits of structured communication strategies. Future research should build on these insights by incorporating techniques to overcome cultural and linguistic barriers in diagnostic model development.

5.2.6. Evaluating Long-Term Impact

Conducting longitudinal studies to evaluate the long-term impact of diagnostic models is essential for understanding their effectiveness over time. Future research should track the impact of these tools on patient outcomes, patient-doctor relationships, and overall healthcare delivery. This will provide valuable insights into how diagnostic models perform in real-world settings and inform future improvements.

Related WorkWoehrle, et al. [22] and Charteris and Pounds [26] provides insights into the long-term effects of healthcare interventions. Woehrle's study Woehrle, et al. [22] on telemonitoring highlights the benefits of long-term patient management strategies. Charteris's work Charteris and Pounds [26] on heart failure management emphasizes tracking outcomes over extended periods. Future studies should build on these findings by evaluating the long-term impact of diagnostic models on patient care and healthcare delivery.

5.2.7. Exploring Technological Advancements

Integrating emerging technologies, such as artificial intelligence (AI) and machine learning, offers significant potential for enhancing diagnostic models. Future research should explore how these technologies can be applied to improve diagnostic accuracy, patient engagement, and overall healthcare delivery. This includes investigating the potential of AI-driven tools to enhance diagnostic performance and support patient-doctor communication.

Related works Deshpande, et al. [23] and Milliren, et al. [25] illustrate the impact of technology on healthcare tools. Deshpande, et al. [23] on opioid management apps highlights the potential of technology to improve patient engagement. Milliren & Roberts's research Milliren, et al. [25] on hemophilia care underscores the benefits of integrating patient feedback and technology. Future studies should explore how advanced technologies can be leveraged to enhance diagnostic models and patient interactions.

Table 3. provides a summary of the identified research gaps and corresponding future directions. These findings underscore key areas for further investigation and enhancement in diagnostic models and patient-doctor communication. By addressing the current gaps in the literature and incorporating advanced technologies, diverse datasets, and user feedback, future research can improve the effectiveness and applicability of diagnostic tools. Moreover, overcoming cultural and linguistic barriers and ensuring the seamless integration of these tools within healthcare systems will be essential for advancing patient care and overall healthcare delivery.

Table 3.
Summary of Research Gaps and Future Directions in AI-Driven Healthcare Communication.

Author(s)	Gap Identified	Future Direction
Woehrle, et al. [22]	Low specificity in diagnostic models	Develop advanced algorithms to improve specificity
Asan, et al. [27]	Integration challenges with EHR systems	Explore strategies for better integration of diagnostic tools
Deshpande, et al. [23]	Limited generalizability of tools	Use diverse datasets to improve generalizability
Milliren, et al. [25]	Need for user feedback in tool development	Incorporate user feedback into model design
Polinski, et al. [28]	Cultural and linguistic barriers	Develop multilingual and culturally sensitive tools
Neu, et al. [24]	Limited long-term impact evaluation	Conduct longitudinal studies on diagnostic models
Charteris and Pounds [26]	Need for advanced technology integration	Investigate AI and machine learning applications

These directions address current limitations and align with ongoing advancements in healthcare technology, promising to enhance diagnostic accuracy, patient engagement, and the quality of patient-doctor interactions.

5.3. Practical Example

In patient-doctor communication, practical applications of technology are becoming increasingly prominent. Two notable examples are the use of WhatsApp in orthopedic trauma care and WeChat for patient communication in China.

WhatsApp, a widely used instant messaging application, has been integrated into orthopedic care to streamline communication and enhance patient management. This technology facilitates orthopedic care aspects, from initial triage to post-operative follow-up. The application supports real-time communication, allowing healthcare teams to quickly share patient images and status updates, improving provider decision-making efficiency and coordination. Additionally, WhatsApp plays a significant role in educational settings, supporting virtual fracture clinics and providing real-time feedback to junior physicians. However, while WhatsApp offers advantages such as real-time communication and broad accessibility, it also presents challenges, including concerns about patient privacy and the potential for misinformation due to limitations in image quality [29].

In China, WeChat serves as a key platform for patient-doctor interactions. This social networking application is widely adopted by healthcare professionals for managing consultations, follow-ups, and patient inquiries. The integration of WeChat into healthcare communication leverages its widespread use and familiarity among doctors and patients, facilitating seamless and informal communication. This is particularly effective in urban areas with high smartphone penetration. Despite its benefits, such as high engagement and versatility, WeChat also poses challenges related to maintaining professional boundaries and dealing with variability in app preferences among different doctors and institutions [30].

Both cases illustrate how integrating familiar technology into healthcare practices can enhance patient-doctor communication. WhatsApp and WeChat each offer unique advantages and face specific challenges, underscoring the importance of balancing the benefits of technological convenience with the need for professional and privacy considerations.

These two types of research do not thoroughly explore how cultural and regional differences impact the effectiveness of WhatsApp and WeChat. The studies primarily focus on specific regions, and there is a need for broader research to understand how these tools perform in different cultural contexts. Different regions may have varying preferences and norms regarding communication, which could affect the adoption and effectiveness of these technologies.

In summary, while technologies like WhatsApp and WeChat hold the potential for improving patient-doctor communication, addressing these gaps is essential for their practical and equitable implementation in healthcare settings. Future research and development efforts should focus on enhancing privacy protections, integrating with healthcare systems, establishing guidelines, providing training, demonstrating efficacy, addressing accessibility issues, and considering cultural variations to optimize the use of these communication tools.

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Institutional Review Board Statement:

This study was conducted using ethical guidelines for research involving human participants. Ethical approval was obtained from the Institutional Review Board (IRB) of Pusan National University Hospital, under approval number IRB No: 2303-004-124. The IRB authorized using anonymized patient data for research purposes from March 10, 2023, to March 6, 2025. As the data were fully anonymized and did not involve direct patient interaction, informed consent was not required by institutional and national ethical regulations.

Transparency:

The author confirms that the manuscript is an honest, accurate and transparent account of the study that no vital features of the study have been omitted and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Competing Interests:

The authors declare that they have no competing interests.

Authors' Contributions:

All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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