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Exploring Barriers and Facilitators of Inter-Professional Communication in Health IT-Supported Patient-Centered Care Systems

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ABSTRACT

Interprofessional communication is essential for improving care coordination, patient safety, healthcare quality, and collaborative decision-making in Health IT-supported patient-centered care systems. Effective communication among healthcare professionals can reduce clinical errors and enhance patient outcomes, while communication barriers may negatively affect healthcare delivery. This study aims to explore barriers and facilitators to inter-professional communication in Health IT-supported patient-centered care systems using machine-learning and deep-learning classification models. For this research, a primary dataset was developed containing 3,000 records with 28 variables, including demographic characteristics, professional roles, Health IT utilization factors, communication practices, organizational support factors, workflow integration measures, and patient-centered care indicators. The study applied supervised machine learning and deep learning methods using a 70% training, 15% validation, and 15% testing split. Three classification models—Neural Network, BiLSTM, and CNN-BiLSTM—were used to classify Barrier Level and Facilitator Level into High, Moderate, and Low categories. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and precision-recall analysis. The results show that the Neural Network model achieved the highest overall performance with an average accuracy of 97.33%, focusing on Facilitator Level classification, which achieved 94.67% accuracy. CNN-BiLSTM achieved an average accuracy of 94.33%, while BiLSTM achieved 84.89% accuracy. The findings suggest that Health IT usability, interoperability, workflow integration, communication openness, role clarity, team trust, training quality, and technical support are important factors influencing interprofessional communication outcomes. The study concludes that machine learning-based classification models can effectively identify communication barriers and facilitators and support improved collaboration, communication effectiveness, and patient-centered care delivery in Health IT-supported healthcare environments.

INTRODUCTION

Interprofessional communication is essential for improving care coordination, patient safety, healthcare quality, and collaborative decision-making in patient-centered healthcare systems. Effective communication among healthcare professionals supports integrated care delivery and contributes to better patient outcomes. However, communication challenges and fragmented healthcare processes continue to affect the quality and efficiency of healthcare services(Vrijhoef *et al.*, 2017).The growing adoption of Health Information Technology (Health IT), including electronic health records, telemedicine platforms, and clinical information systems, has created new opportunities for enhancing communication and collaboration among healthcare professionals. Health IT can improve information sharing, care coordination, and clinical decision-making, but technological and operational challenges may also influence communication outcomes(Wu *et al.*, 2025).In addition to technological factors, organizational and professional factors such as leadership support, teamwork, communication openness, and role clarity play important roles in strengthening interprofessional collaboration. Effective leadership and collaborative practices are essential for supporting integrated and patient-centered healthcare delivery (Liddy *et al.*, 2014; Nieuwboer *et al.*, 2019).Previous studies have explored integrated care, teamwork communication, and patient-centered healthcare environments. However, limited research has applied machine learning and deep learning techniques to identify communication barriers and facilitators in Health IT-supported patient-centered care systems (Kylén *et al.*, 2025; Mater *et al.*, 2018). Therefore, this study explores barriers and facilitators of interprofessional communication using machine learning and deep learning classification models and compares the performance of Neural Network, CNN-BiLSTM, and BiLSTM models.

LITERATURE REVIEW

Recent Developments in Health IT-Supported Patient-Centered Care

Recent developments in Health Information Technology (Health IT) have significantly improved patient-centered care and interprofessional collaboration in healthcare systems. Technologies such as electronic health records, telehealth platforms, mobile health applications, artificial

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intelligence, and digital communication systems support information sharing, clinical decision-making, care coordination, and healthcare service management (Engelseth *et al.*, 2021; Maudsley *et al.*, 2019). Health IT also enables healthcare professionals to access clinical information more efficiently and improve communication across different care settings.In addition, recent studies show that digital health technologies can strengthen patient engagement, shared decision-making, collaborative care, and communication effectiveness. Telehealth and web-based communication systems have improved patient-family-provider interaction, while implementation-focused healthcare initiatives have emphasized the importance of teamwork and stakeholder engagement in healthcare delivery (Rosenthal *et al.*, 2024; Williams *et al.*, 2022). Furthermore, artificial intelligence has demonstrated significant potential for improving diagnostic accuracy, workflow efficiency, and healthcare decision-making, although challenges related to privacy, user acceptance, and system integration remain important concerns (Qi *et al.*, 2025; Schuster *et al.*, 2018).

Theoretical and Practical Foundations of Interprofessional Communication

Effective interprofessional communication in Health IT-supported healthcare systems is influenced by several organizational, technological, and human factors. Previous studies have shown that digital tools, mobile technologies, and electronic communication platforms can improve information sharing, clinical decision-making, and collaboration among healthcare professionals when appropriately integrated into clinical workflows (Maudsley *et al.*, 2019). Similarly, web- and mobile-assisted healthcare interventions have been reported to strengthen communication, treatment coordination, and patient engagement across healthcare teams (Schuster *et al.*, 2018). Successful implementation of Health IT systems also depends on stakeholder engagement, leadership support, professional education, and organizational readiness (Williams *et al.*, 2022; Simmons *et al.*, 2026). Educational reforms and competency-based training programs can enhance healthcare professionals' preparedness for collaborative practice and patient-centered care (Vanhanen *et al.*, 2026). Furthermore, emerging technologies such as artificial intelligence and electronic decision-support systems have demonstrated potential to improve healthcare communication, clinical efficiency, and shared decision-making, although challenges related to trust, usability, and technology adoption remain important considerations (Qi *et al.*, 2025; Junius-Walker *et al.*, 2021). Public policy support and interdisciplinary collaboration also play important roles in strengthening communication within healthcare systems (Coffman *et al.*, 2011).

Challenges in Health IT-Supported Interprofessional Communication

Despite the growing adoption of Health IT systems, several challenges continue to affect interprofessional communication in patient-centered healthcare environments. Previous studies have identified barriers such as limited interoperability, inadequate communication workflows, insufficient professional training, lack of organizational support, cultural competency gaps, and restricted access to healthcare resources, which may negatively influence collaboration and care coordination among healthcare professionals (Junius-Walker *et al.*, 2021; Milkins *et al.*, 2026). In addition, ineffective team integration and insufficient interprofessional education can hinder communication effectiveness and collaborative decision-making in healthcare settings(Belleza & Johnson, 2023). These challenges highlight the need for improved Health IT infrastructure, workforce training, and organizational strategies to support effective interprofessional communication and patient-centered care.

Limitations of Current Machine Learning-Based Communication Research

Although Health Information Technology has improved communication and collaboration in healthcare, several limitations remain in current communication research. Studies have reported challenges related to EMR/EHR usability, interoperability, and data management, which may affect effective interprofessional collaboration(Kosteniuk *et al.*, 2024). Similarly, communication platforms may improve teamwork, but issues such as information overload, fragmented workflows, and user adoption continue to influence communication effectiveness(Nie *et al.*, 2023). Existing research has also emphasized the need for improved professional training and collaborative learning environments to support communication practices (Langendyk *et al.*, 2016). Furthermore, healthcare studies have identified barriers associated with accessibility, language, and organizational factors that may affect patient-centered communication outcomes (Smith *et al.*, 2025). While previous studies have explored various healthcare communication challenges, limited research has applied machine learning and deep learning models to simultaneously classify communication barriers and facilitators in Health IT-supported patient-centered care systems.

Research Gap

Although Health Information Technology (Health IT) is widely used to support patient-centered care and interprofessional collaboration, limited studies have applied machine learning and deep learning models to identify communication barriers and facilitators simultaneously. Previous research mainly focused on Health IT adoption, communication challenges, and care coordination, while fewer studies classified communication outcomes using multiple Health IT, organizational, and communication-related factors. Therefore, this study addresses this gap by applying classification models to identify communication barriers and facilitators in Health IT-supported patient-centered care systems.

Research Questions

1. How can machine learning models support the identification of communication barriers and facilitators in Health IT-supported patient-centered care systems?
2. Which Health IT and communication-related factors influence communication outcomes?
3. How can machine learning models classify Barrier Levels and Facilitator Levels?
4. Which classification model performs best in predicting communication outcomes?
5. How can machine learning-based prediction support improved interprofessional communication in healthcare systems?

Research Objectives

1. The main objective of this study is to explore barriers and facilitators of interprofessional communication in Health IT-supported patient-centered care systems using machine learning models.
2. Specifically, the study aims to:
3. To examine the role of machine learning models in identifying communication barriers and facilitators.
4. To identify key Health IT and communication-related factors that influence communication outcomes.
5. To apply machine learning models for classifying Barrier Levels and Facilitator Levels.

MATERIALS AND METHODS

Study Area

This study was conducted in the context of Health IT-supported patient-centered care systems, where effective interprofessional communication is essential for improving care coordination, patient safety, healthcare quality, and collaborative decision-making. The study focused on identifying communication barriers and facilitators among healthcare professionals working in technology-enabled healthcare environments.

Study Design

This study followed a quantitative and machine learning-based research design. The main purpose of the study was to classify communication barriers and facilitators in Health IT-supported patient-centered care systems using machine learning and deep learning models. The target variables of the study were Barrier Level and Facilitator Level, which were classified into three categories: High, Moderate, and Low.

Sample Size and Selection

For this research, a synthetic dataset was developed containing 3,000 healthcare-related records and 28 variables. The dataset included demographic characteristics, professional background, Health IT usage factors, communication-related indicators, organizational support measures, workflow integration variables, and patient-centered care outcomes. The dataset was divided into training, validation, and testing sets using a 70%, 15%, and 15% split. This allowed the models to learn from training data, optimize performance using validation data, and evaluate final performance on unseen test data.

Measures and Variables

The major variables used in this study included profession, care setting, age, gender, years of experience, EHR use frequency, secure messaging use, telehealth use, Health IT training quality, interoperability, system usability, technical support, leadership support, workflow integration, data accuracy, alert fatigue, information overload, privacy concern, role clarity, team trust, communication openness, handoff quality, interprofessional communication effectiveness, patient-centered care, and overall satisfaction. The dependent variables were Barrier Level and Facilitator Level. The independent variables were used as predictors for developing machine learning and deep learning classification models.

Data Collection Procedure

The dataset was organized in a structured format to represent communication experiences and Health IT utilization patterns among healthcare professionals. Before applying the machine learning models, the dataset was prepared and transformed for analysis. Relevant communication, organizational, and Health IT-related variables were selected so that the models could identify important patterns associated with communication barriers and facilitators.

Research Tools and Techniques

Three classification models were applied in this study: Neural Network, BiLSTM, and CNN-BiLSTM. These models were selected because they are effective for complex classification tasks and can identify nonlinear relationships among communication, organizational, and Health IT-related variables. The models were used to classify Barrier Level and Facilitator Level into High, Moderate, and Low categories.

Data Analysis Techniques

The performance of the models was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision–recall curve, and feature importance analysis. The Neural Network model achieved the highest performance, obtaining 100% accuracy for Barrier Level classification and 94.67% accuracy for Facilitator Level classification, resulting in an average accuracy of 97.33%. CNN-BiLSTM achieved an average accuracy of 94.33%, while BiLSTM achieved 84.89% accuracy. Therefore, further analysis was mainly focused on the Neural Network model.

RESULTS AND DISCUSSION

Classification Performance of the Neural Network Model

The study applied three classification models: Neural Network, CNN-BiLSTM, and BiLSTM. Among these models, the Neural Network achieved the highest overall classification performance with an average accuracy of

97.33%. CNN-BiLSTM achieved an average accuracy of 94.33%, while BiLSTM achieved 84.89% accuracy. Although the Neural Network achieved perfect classification performance for Barrier Level prediction, further analysis was mainly focused on Facilitator Level classification, which achieved 94.67% accuracy and provided a more realistic evaluation of model performance. Therefore, the Neural Network model was selected as the best-performing model, and the detailed results and analysis below are presented for this model in Table 1.

The results indicate that the Neural Network model outperformed the other models and demonstrated strong

Table 1: Performance Comparison of Classification Models

Model	**Barrier Level Accuracy (%)**	**Facilitator Level Accuracy (%)**	**Average Accuracy (%)**
Neural Network	100.00	94.67	97.33
CNN-BiLSTM	96.67	92.00	94.33
BiLSTM	77.78	92.00	84.89

capability in classifying communication outcomes in Health IT-supported patient-centered care systems.

Confusion Matrix of the Neural Network Model

The confusion matrix was used to evaluate the classification performance of the Neural Network model for Facilitator Level prediction. It shows the distribution of correctly and incorrectly classified samples across High, Low, and Moderate categories, helping to identify the model's prediction reliability.

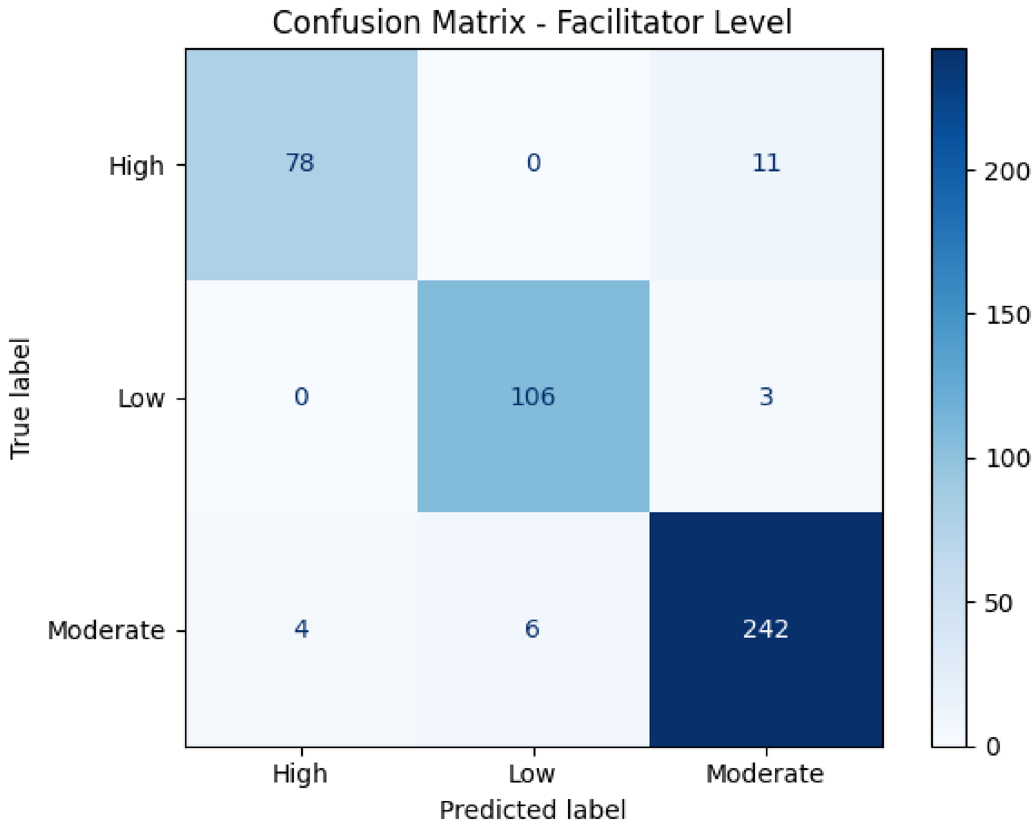

Figure 1: Confusion Matrix of the Neural Network Model

Fig. 1 shows the confusion matrix of the Neural Network model for Facilitator Level classification. The model correctly classified 78 High-level facilitator cases, 106 Low-level facilitator cases, and 242 Moderate-level facilitator cases. A small number of observations were misclassified between the classes, resulting in an overall accuracy of 94.67%. Most predictions were concentrated along the diagonal of the confusion matrix, indicating strong classification performance and reliable identification of facilitator levels.

Multi-Class ROC Curve of the Neural Network Model

The multi-class ROC curve was generated to assess the model's ability to distinguish among different facilitator levels. This curve provides a visual representation of the true positive rate and false positive rate for each class, indicating the discriminative strength of the model.

Fig. 2 presents the ROC curve for Facilitator Level classification. The model achieved very high AUC values for all classes, including High (AUC = 0.994), Low (AUC = 0.998), and Moderate (AUC = 0.988). These results demonstrate excellent discrimination capability and indicate that the Neural Network model effectively distinguished between different facilitator categories.

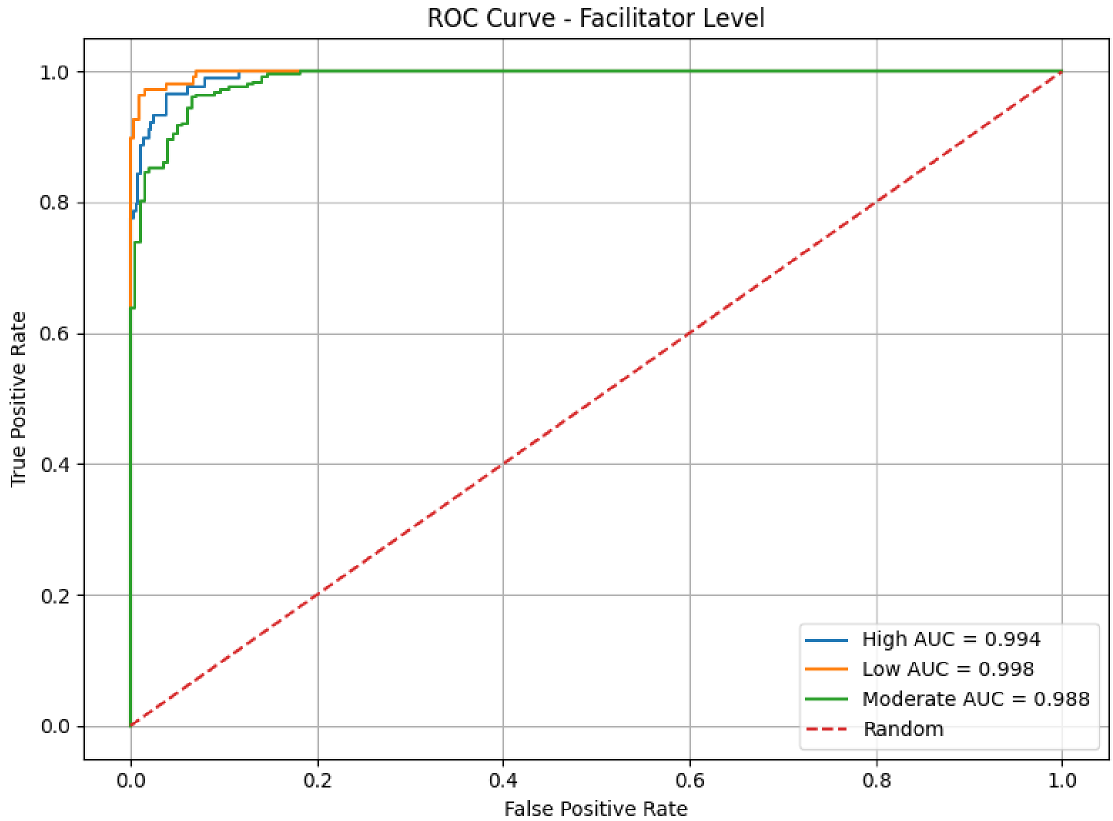

Figure 2: Multi-Class ROC Curve of the Neural Network Model

Precision–Recall Curve of the Neural Network Model

The precision–recall curve was used to examine the balance between precision and recall across the facilitator

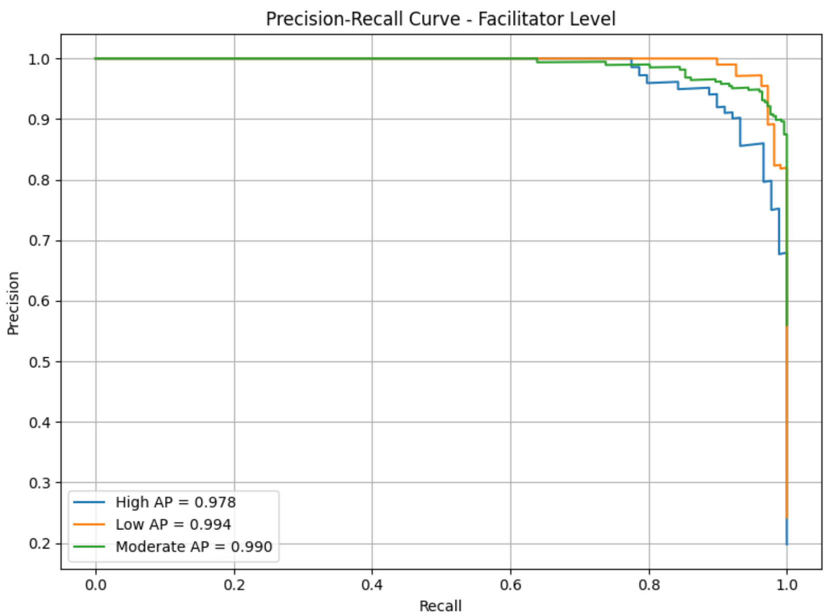

Figure 3: Precision–Recall Curve of the Neural Network Model

categories. This evaluation is particularly useful for understanding how reliably the model identifies each class while minimizing false predictions.

Fig. 3 shows the precision–recall curve of the Neural Network model. The average precision values were 0.978 for the High class, 0.994 for the Low class, and 0.990 for the Moderate class. These results indicate high predictive reliability and balanced classification performance across all facilitator categories.

Top 20 Feature Importance of the Neural Network Model

Feature importance analysis was conducted to identify the most influential variables affecting Facilitator Level classification. The top-ranked features help explain which Health IT, organizational, and communication-related factors contributed most to the model's prediction outcomes.

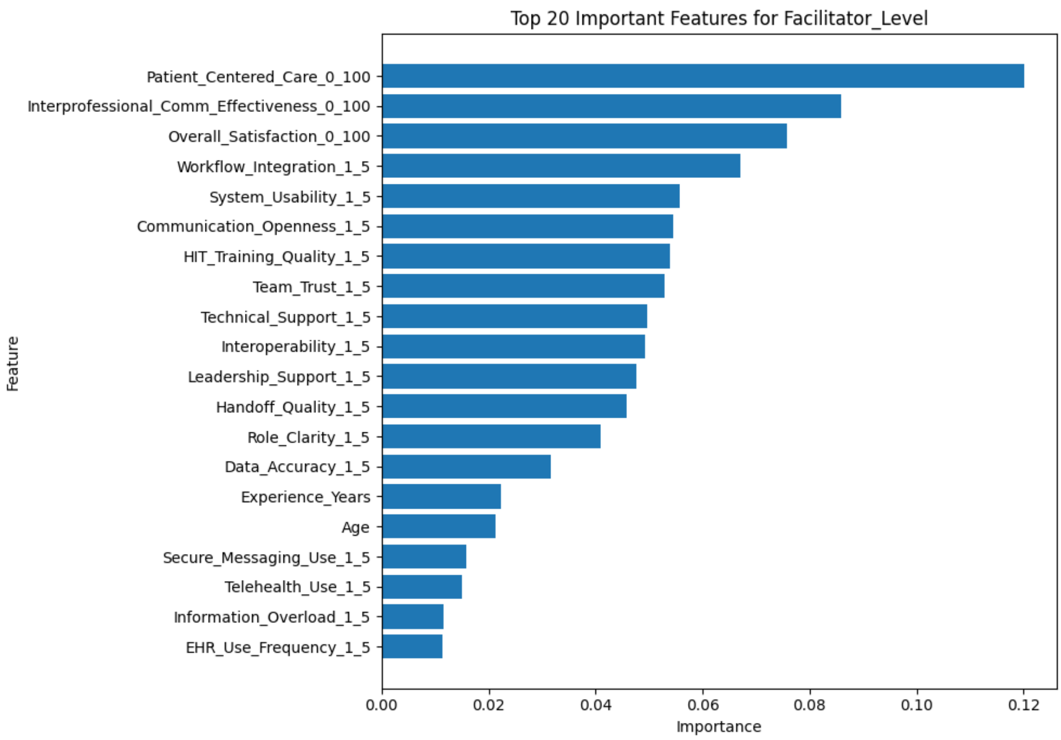

Figure 4: Top 20 Feature Importance Variables.

Fig. 4 shows the top 20 feature importance values generated by the Neural Network model. The most influential features included Information_Overload, Alert_Fatigue, Privacy_Concern, Interprofessional_Communication_Effectiveness, Patient_Centered_Care, Overall_Satisfaction, Leadership_Support, Technical_Support, Interoperability, and HIT_Training_Quality. These findings suggest that both Health IT-related and organizational factors play important roles in influencing communication outcomes in patient-centered care systems.

Discussion

This study explored barriers and facilitators of interprofessional communication in Health IT-supported patient-centered care systems using machine learning and deep learning models. The results showed that the Neural Network model achieved the highest classification performance, indicating the effectiveness of machine learning approaches in identifying communication outcomes.The findings suggest that Health IT factors, including system usability, interoperability, and technical support, play important roles in improving communication and patient-centered care. Similar findings have been reported in studies highlighting the importance of information technology in supporting healthcare services and professional collaboration(Westerling, 2011). The study also identified communication openness, role clarity, team trust, and leadership support as important facilitators of interprofessional communication. These findings are consistent with previous research emphasizing shared decision-making, patient-centered care, and collaborative healthcare practices (Friesen-Storms *et al.*, 2018).Furthermore, information overload, alert fatigue, and privacy concerns were identified as major communication barriers. Previous studies have similarly reported that technological and workflow-related challenges may affect communication effectiveness and healthcare delivery(Rosenthal *et al.*, 2024).The results further indicate that machine learning-based approaches can effectively classify communication outcomes and support healthcare decision-making. Similar evidence has been reported in studies focusing on patient-centered interventions, communication support, and healthcare management strategies (Sugumaran *et al.*, 2024).In addition, effective communication remains essential for improving patient engagement, care coordination, and healthcare outcomes, particularly in technology-supported healthcare environments (Smith Bachman, 2022). Overall, the findings demonstrate that machine learning models can support the identification of communication barriers and facilitators and contribute to improved interprofessional communication and patient-centered care.

Findings

1. The Neural Network model achieved the highest classification performance among all models.
2. Communication barriers and facilitators were successfully classified into High, Moderate, and Low categories.
3. Information overload, alert fatigue, and privacy concern were important predictors of communication outcomes.
4. Health IT and organizational factors significantly influenced communication barriers and facilitators.
5. Machine learning-based prediction can support improved interprofessional communication and patient-centered care delivery.

Recommendations

1. Healthcare organizations should prioritize reducing information overload and alert fatigue to minimize communication barriers.
2. Enhance Health IT usability, interoperability, and training quality to improve communication facilitators.
3. Strengthen leadership support, technical support, and workflow integration to promote effective interprofessional communication.
4. Encourage role clarity, team trust, and communication openness to enhance facilitator outcomes.
5. Apply machine learning-based tools to monitor and predict communication barriers and facilitators in patient-centered care systems.

Limitations

1. The study used a synthetic dataset, which may not fully represent real-world interprofessional communication scenarios in all healthcare settings.
2. Only selected Health IT, organizational, and communication-related variables were considered; other potential factors influencing communication outcomes may have been omitted.
3. The study focused on three classification models; other advanced or hybrid machine learning models were not evaluated.

CONCLUSIONS

This study examined the barriers and facilitators of interprofessional communication in Health IT-supported patient-centered care systems using machine learning and deep learning classification models. The results show that communication outcomes can be effectively classified using factors such as information overload, alert fatigue, privacy concerns, interprofessional communication effectiveness, patient-centered care practices, leadership support,technical support, interoperability, workflow integration, and Health IT training quality. Among the three models, the Neural Network achieved the highest performance, with 100% accuracy for Barrier Level classification and 94.67% accuracy for Facilitator Level classification, resulting in an average accuracy of 97.33%. Therefore, this study concludes that machine learning-based classification models can effectively identify communication barriers and facilitators and support improved collaboration, communication effectiveness, and patient-centered care delivery in Health IT-supported healthcare environments.

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