Coordinating Care in Fragmented Systems: A Digital Platform Approach to Rural Healthcare Delivery in Rural Bangladesh

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Abstract
Rural healthcare delivery in Bangladesh remains challenged by fragmented services, limited specialist access, delayed referrals, poor information sharing, and weak coordination between patients, community health workers, clinics, and hospitals. This study aimed to evaluate how a digital health platform can improve coordinated care delivery in rural Bangladesh and to predict the overall impact of such a platform using machine learning techniques. A dataset was developed based on rural healthcare service factors related to digital platform use, care coordination, patient access, communication, service efficiency, and perceived healthcare impact. The target variable was the Overall Impact of Digital Health Platform, classified into five categories: No impact, Low impact, Moderate impact, High impact, and Very high impact. Four machine learning models were applied using an 80/20 train-test split: Random Forest, XGBoost, LightGBM, and Artificial Neural Network using Scikit-Learn MLPClassifier. Model performance was evaluated through accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision-recall curve, learning curve, validation curve, calibration curve, and feature importance analysis. The Random Forest model achieved 82% accuracy, XGBoost achieved 94% accuracy, LightGBM achieved 98% accuracy, and the ANN model achieved the best performance with 99% accuracy, precision, recall, and weighted F1-score. The findings indicate that advanced machine learning models, particularly ANN and LightGBM, can effectively predict the impact of digital health platforms in rural healthcare systems. The results suggest that digital platform-based coordination can support improved healthcare accessibility, communication, decision-making, and service integration in rural Bangladesh. This study concludes that machine learning-supported digital health platforms may provide a practical approach for strengthening fragmented rural healthcare delivery systems.

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Keywords: Rural healthcare, Digital health platform, Care coordination, Machine learning, Bangladesh, Healthcare delivery

1. Introduction

Rural healthcare delivery has become an important concern in Bangladesh because fragmented services, limited specialist access, delayed referral, poor communication, and weak coordination often reduce the quality and continuity of care. Digital health platforms offer a practical solution by connecting patients, community health workers, clinics, and hospitals through better information sharing, remote consultation, monitoring, and data-based decision-making. Recent studies show that digital diagnostics and virtual care platforms can improve primary healthcare access and efficiency in low-resource settings (Forkuo *et al*., 2022), while rural digital health practices can support chronic disease management even in low-internet environments (Olu James Mbanugo, 2020). In Bangladesh, digital interventions have improved rural health service use and patient

outcomes(Ferdaus, 2024), decentralized digital care has supported hypertension and diabetes management (Xie *et al*., 2023) and digital registers have strengthened maternal and newborn care data systems (Jabeen *et al*., 2024). Health data linkage and DHIS2-based systems can also improve policy planning and evidence-based implementation (Sarker *et al*., 2024), while digital health insurance may support health expenditure management and health security (Md. Shafiul Alam Bhuiyan & Md. Ziaur Rahman, 2024). However, digital transformation in Bangladesh still faces barriers such as poor internet connectivity, limited digital literacy, weak infrastructure, data privacy concerns, and uneven adoption (Taher *et al*., 2025; Tania & Clifton, 2023). Climate-related health risks further highlight the need for resilient, equitable, and technology-enabled healthcare systems in Bangladesh (Mamun & Kayenat, 2026). Therefore, this study evaluates how a digital health platform can improve coordinated care delivery in fragmented rural healthcare systems in Bangladesh and applies machine learning models to predict the overall impact of the platform.

2. Literature Review

2.1. Recent Developments in Digital Health Platforms for Rural Healthcare Delivery

Recent developments in digital health show that rural healthcare delivery is gradually moving toward more connected, accessible, and data-driven systems. In Bangladesh, eHealth initiatives such as Portable Health Clinic have been used to provide healthcare support to low-income and underserved rural people through electronic health records, medical sensors, and remote doctor consultation(Hossain *et al*., 2017). Smartphone-based mHealth programs have also improved the work of community health workers by helping them collect health data, guide patients, and increase clinic attendance in rural areas(Ginsburg *et al*., 2014). At the national level, multi-stakeholder collaboration has been identified as important for scaling up ICT-based health services and improving coordination among government, private, NGO, and development partners (Ashraf *et al*., 2015). Recent studies also show that mobile diagnostic tools can support rural telemedicine and task-shifting, although high cost, poor training, and weak infrastructure still limit their use (Okazaki *et al*., 2026). In addition, mHealth services can improve women's digital health equity by providing private, convenient, and accessible reproductive health support, but privacy, digital divide, and service quality remain major concerns(Jonayed & Rumi, 2024).

2.2. Theoretical and Practical Foundations of Care Coordination in Rural Health Systems

Care coordination in rural health systems depends on timely communication, referral, follow-up, information sharing, and connection among patients, community health workers, clinics, and doctors. Telemedicine can connect rural patients with doctors through virtual clinics (Khatun *et al*., 2025), while decentralized digital care can support screening, counselling, follow-up, and chronic disease management at lower-level facilities (Xie *et al*., 2023). Digital health training can improve healthcare workers' service capacity(Aktar & Rahman, 2020), and AI can improve decision-making and healthcare access in underserved areas(Makhdum, 2024). Digital health insurance can also support financial protection and integrated healthcare service delivery(Md. Shafiul Alam Bhuiyan & Md. Ziaur Rahman, 2024). Therefore, this study considers digital platform-based care coordination as a way to improve access, communication, referral support, and service efficiency in rural Bangladesh.

2.3. Challenges in Fragmented Rural Healthcare Delivery Systems

Fragmented rural healthcare delivery systems face several challenges, including limited infrastructure, shortage of trained healthcare workers, weak referral pathways, poor communication, and inadequate access to diagnostic technologies. In developing economies, equipment shortages and financing gaps reduce healthcare service readiness, especially in rural facilities (Onabowale, 2020). South Asian primary healthcare systems also face poor preparedness for NCD care due to limited skilled workforce, medicines, technologies, and financing (Ahmed *et al*., 2024). Digital ecosystems can improve communication, but their use is often limited by fragmented digital infrastructure, interoperability problems, privacy concerns, and provider resistance (Mwogosi & Mambile, 2025). Telemedicine can support primary care, but weak internet access, lack of policy support, non-interoperable systems, and poor digital readiness create barriers to scale-up (Gudi *et al*., 2021). Therefore, this study focuses on using a digital health platform to reduce these challenges by improving patient access, referral support, information sharing, service efficiency, and care coordination in rural Bangladesh.

2.4. Limitations of Current Digital Health Platform Research

Current digital health platform research has some limitations in practical implementation, long-term sustainability, and real-world evaluation. Many studies highlight the importance of health workforce strengthening, but rural primary healthcare still faces shortages of trained workers and unequal workforce distribution (Zapata *et al*., 2021). Rural and remote health systems are also often less prepared for emergency response, and digital technology may improve coordination but remains inaccessible for some populations (Dudley *et al*., 2023). Interoperable digital systems can improve patient access and service efficiency, but fragmented data systems, privacy issues, and unequal digital maturity limit wider adoption (Anthony & Dada, 2020). In primary healthcare, co-design and co-production approaches can improve people-centered services, but evidence on long-term impact and sustainability is still limited (Dingelstad *et al*., 2025). Similarly, rural communication technologies such as MANETs may improve real-time data sharing, but practical barriers such as poor infrastructure, power supply, technical capacity, and pilot-level evidence remain important limitations(Mabina *et al*., 2024). Therefore, more evidence is needed on scalable, sustainable, and machine learning-supported digital health platforms for improving rural care coordination in Bangladesh.

2.5. Research Gap

Although digital health platforms are used in healthcare delivery, limited studies have focused on their role in improving care coordination in fragmented rural healthcare systems in Bangladesh. Previous studies mostly discussed telemedicine or digital health adoption, but fewer studies used machine learning to predict the overall impact of digital health platforms. Therefore, this study addresses this gap by

applying machine learning models to classify the impact of a digital health platform in rural healthcare delivery.

2.6. Research Questions

1. How can a digital health platform improve care coordination in rural healthcare delivery?
2. Which healthcare service factors influence the impact of a digital health platform?
3. How can machine learning models classify the impact of digital health platforms?
4. Which machine learning model performs best in predicting platform impact?
5. How can digital health platforms support better healthcare access and service integration?

2.7. Research Objectives

The main objective of this study is to evaluate the impact of a digital health platform on coordinated rural healthcare delivery in Bangladesh using machine learning techniques. Specifically, the study aims to:

1. To examine the role of digital health platforms in improving rural care coordination.
2. To identify key healthcare service factors related to platform impact.
3. To apply machine learning models for impact classification.
4. To compare model performance and identify the best-performing model.
5. To assess how digital health platforms support healthcare access and service integration.

3. Materials and Methods

3.1. Study Area

This study was conducted in the context of rural healthcare delivery systems in Bangladesh, where healthcare services are often fragmented due to limited specialist access, delayed referrals, weak coordination, and poor information sharing. The study focuses on how a digital health platform can support better communication and coordination among patients, community health workers, clinics, and hospitals.

3.2. Study Design

This study followed a quantitative and machine learning-based research design. The main purpose was to evaluate the impact of a digital health platform on rural healthcare delivery and to classify the overall impact into different categories. The target variable was the Overall Impact of Digital Health Platform, which was classified into five categories: No impact, Low impact, Moderate impact, High impact, and Very high impact.

3.3. Sample Size and Selection

The dataset was developed based on rural healthcare service factors related to digital platform use, care coordination, patient access, communication, service efficiency, and perceived healthcare impact. The dataset was divided into training and testing subsets using an 80/20 train-test split. This allowed the models to be trained on one portion of the data and evaluated on unseen test data.

3.4. Measures and Variables

The major variables included digital platform use, care coordination, patient access, communication, service efficiency, referral support, information sharing, and perceived healthcare impact. The dependent variable was the overall impact of the digital health platform. The independent variables were used as predictors for machine learning model development.

3.5. Data Collection Procedure

The data were organized in a structured format to represent rural healthcare delivery conditions in Bangladesh. Before applying the machine learning models, the dataset was cleaned and prepared for analysis. The variables were arranged properly so that the models could identify patterns related to digital healthcare coordination and overall platform impact.

3.6. Research Tools and Techniques

Four machine learning models were applied in this study: Random Forest, XGBoost, LightGBM, and Artificial Neural Network using Scikit-Learn MLPClassifier. These models were used to predict the overall impact level of the digital health platform. Among the models, ANN achieved the best performance and was selected for further detailed evaluation.

3.7. Data Analysis Techniques

The performance of the models was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision-recall curve, learning curve, validation curve, calibration curve, and feature importance analysis. Random Forest achieved 82% accuracy, XGBoost achieved 94%, LightGBM achieved 98%, and ANN achieved the highest accuracy of 99%. Therefore, the ANN model was considered the best-performing model for predicting the impact of digital health platforms in rural healthcare delivery. Table 1 summarizes the main components of the research design, including the dataset type, selected features, data split, output classes, applied models, best-performing model, and evaluation measures.

Table 1: Summary of the Research Design

Item	Details
Data	Rural healthcare service-based dataset
Features	Digital platform use, care coordination, patient access, communication, service efficiency, referral support, information sharing, and perceived healthcare impact
Method	Quantitative machine learning-based approach
Split	80% training, 20% testing
Output	Overall impact classification of digital health platform
Classes	No impact, Low impact, Moderate impact, High impact, Very high impact
Models	Random Forest, XGBoost, LightGBM, ANN
Best Model	ANN
Measures	Accuracy, Precision, Recall, F1-score, Confusion Matrix, ROC Curve, Precision–Recall Curve

4. Results and Analysis

4.1. Model Performance Comparison

In this study, four machine learning models were applied to evaluate the overall impact of a digital health platform in rural healthcare delivery in Bangladesh. The models used were Random Forest, XGBoost, LightGBM, and Artificial Neural Network (ANN). Among these models, Random Forest achieved an accuracy of 82%, XGBoost achieved 94%, LightGBM achieved 98%, and ANN achieved the highest accuracy of 99%. Since the ANN model provided the best classification performance, the further evaluation and analysis were mainly focused on the ANN model. The ANN model was evaluated using several performance evaluation techniques, including classification report, confusion matrix, ROC curve, precision-recall curve, learning curve, validation curve, calibration curve, loss curve, validation accuracy curve, and permutation-based feature importance. These evaluation results helped to understand the reliability, prediction ability, and overall effectiveness of the ANN model in classifying the impact levels of the digital health platform. Table 2 presents the performance comparison of the applied machine learning models, where ANN achieved the highest accuracy of 99%, followed by LightGBM, XGBoost, and Random Forest.

Table 2: Model Performance Comparison

Model	Accuracy	Performance Level	Interpretation
Random Forest	82%	Good	Performed reasonably but lower than the other models.
XGBoost	94%	Very good	Showed strong classification performance.
LightGBM	98%	Excellent	Achieved very high prediction accuracy.
ANN	99%	Best	Achieved the highest accuracy and was selected for further analysis.

4.2. Classification Report Analysis

After selecting the ANN model as the best-performing model, a detailed classification report was generated to evaluate its performance across all impact categories. The ANN model showed excellent predictive capability for all five classes: High impact, Low impact, Moderate impact, No impact, and Very high impact. The model achieved very high precision, recall, and F1-score values for each class, indicating that it was able to correctly identify most of the actual class labels with very few misclassifications. The No impact class achieved perfect performance with a precision, recall, and F1-score of 1.00, while the Low impact class also showed outstanding performance with an F1-score of 1.00. The overall accuracy of the ANN model was 0.99, which demonstrates that the model can reliably classify the overall impact of a digital health platform in rural healthcare delivery. Table 3 presents the detailed classification report of the ANN model, showing its precision, recall, F1-score, and support values for all five impact categories.

Table 3: Classification Report of ANN Model

Impact Class	Precision	Recall	F1-Score	Support
High impact	0.98	0.98	0.98	182
Low impact	0.99	1.00	1.00	166
Moderate impact	0.99	0.99	0.99	189
No impact	1.00	1.00	1.00	179
Very high impact	0.99	0.99	0.99	284
Accuracy			0.99	1000
Macro Average	0.99	0.99	0.99	1000
Weighted Average	0.99	0.99	0.99	1000

4.3. Loss Curve Analysis

The ANN loss curve shows that the training loss decreased sharply within the first few iterations and then became almost stable near zero. This indicates that the model learned the dataset patterns quickly and converged efficiently. The stable curve also suggests strong training performance and effective classification ability. Figure 1 illustrates the loss curve of the ANN model during training, where the training loss decreased rapidly and became stable near zero.

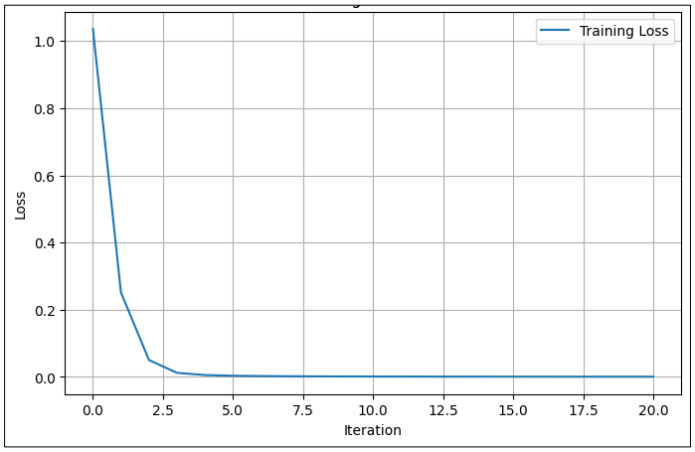

Fig 1: Loss Curve of the ANN Model during Training

4.4. Validation Accuracy Curve Analysis

The validation accuracy curve shows that the ANN model improved rapidly during the initial iterations, increasing from about **0.88** to almost **1.00**. After a few iterations, the accuracy became stable at the highest level, indicating that the model learned effectively and maintained strong validation performance. This confirms that the ANN model achieved excellent generalization ability on unseen data. Figure 2 shows the validation accuracy curve of the ANN model, indicating that the model quickly improved and maintained high validation accuracy.

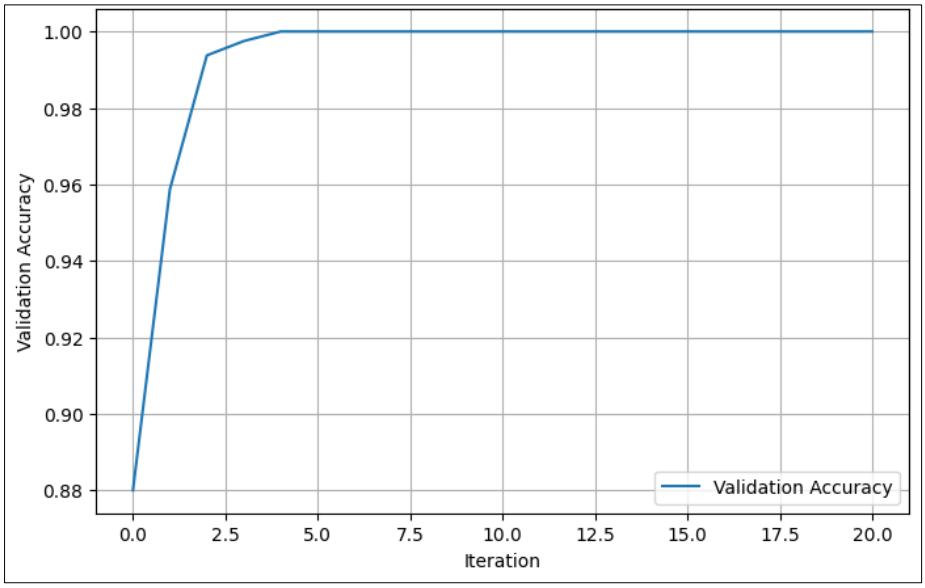

Fig 2: Validation Accuracy Curve of the ANN Model

4.5. Confusion Matrix Analysis

The confusion matrix in Figure 3 shows that the ANN model classified most of the samples correctly across all five impact categories. The diagonal values are very high, such as 179 High impact**,** 166 Low impact**,** 187 Moderate impact**,** 179 No impact and 282 Very high impact correctly predicted. Only a few misclassifications occurred, mainly between High impact, Moderate impact, and Very high impact. This result confirms that the ANN model performed very accurately in predicting the overall impact of the digital health platform.

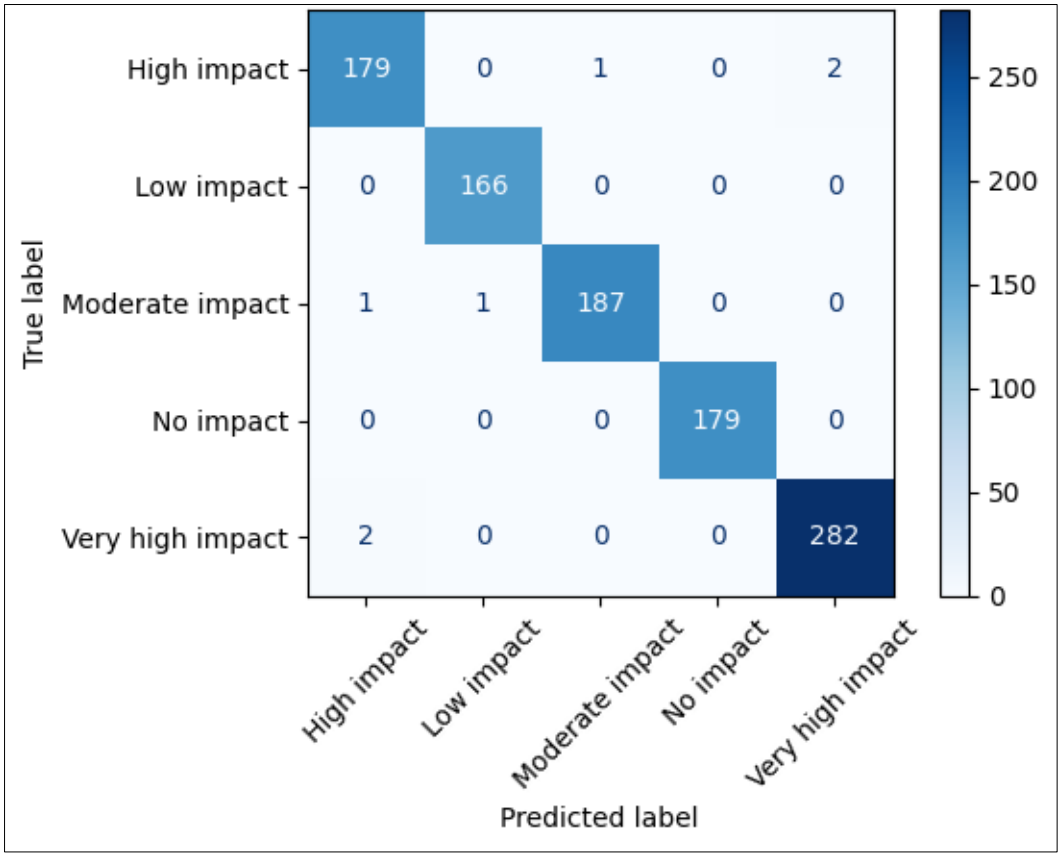

Fig 3: Confusion Matrix of the ANN Model

4.6. ROC Curve Analysis

The multi-class ROC curve in Figure 4 shows the excellent classification ability of the ANN model for all five impact categories. Each class achieved an AUC value of 1.000**,** indicating that the model was highly effective in distinguishing between different impact levels. The ROC curves remain close to the top-left corner, which confirms very high true positive rates and very low false positive rates. Therefore, the ANN model demonstrates strong discriminatory performance for predicting the overall impact of the digital health platform.

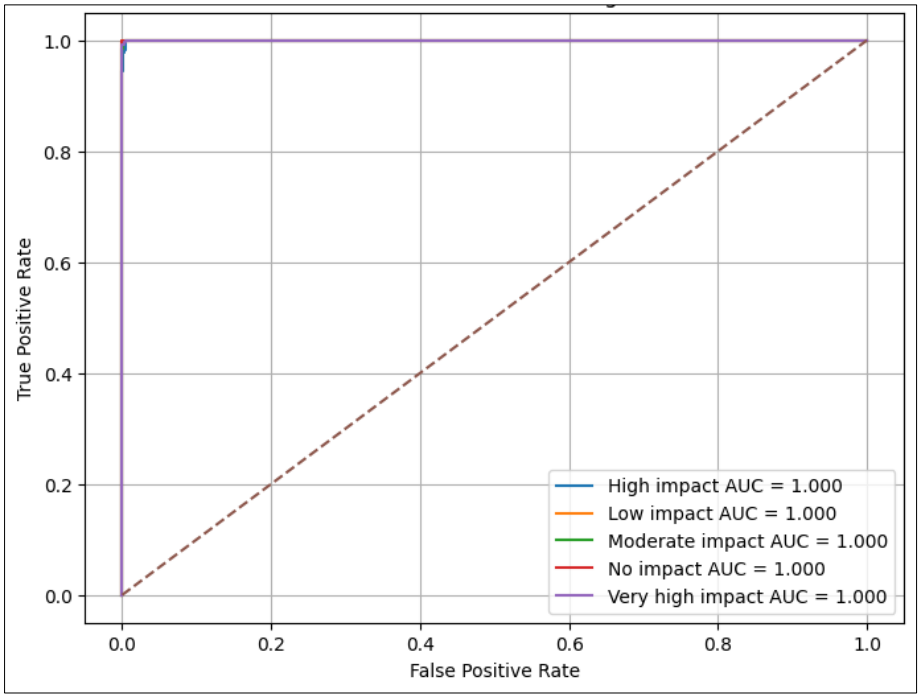

Fig 4: Multi-Class ROC Curve of the ANN Model

4.7. Precision–Recall Curve Analysis

The multi-class Precision–Recall (PR) curve in Figure 5 shows the strong predictive performance of the ANN model across all five impact categories. The average precision (AP) values are almost perfect for all classes, where High impact achieved 0.999, and Low impact, Moderate impact, No impact and Very high impact each achieved 1.000. These results indicate that the ANN model maintained both high precision and high recall in classifying the impact levels, confirming its excellent classification performance.

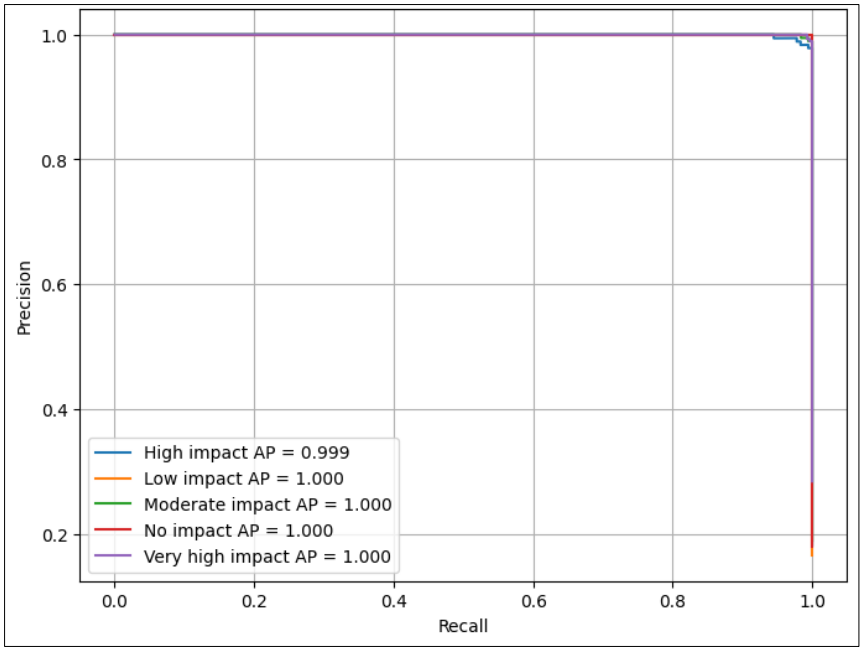

Fig 5: Multi-Class Precision–Recall Curve of the ANN Model

Overall, the results and analysis show that the ANN model performed better than the other machine learning models in predicting the overall impact of the digital health platform. The high accuracy, strong classification report, clear

confusion matrix, excellent ROC curve, and strong precision–recall curve confirm that the ANN model classified all five impact categories effectively. Therefore, the ANN model can be considered the most reliable model in this study for identifying the impact level of digital health platform-based rural healthcare delivery in Bangladesh.

5. Discussion

The findings show that digital health platforms can improve rural healthcare coordination by supporting patient access, communication, referral, service efficiency, and information sharing. Previous studies also show that AI and telehealth can improve diagnosis, remote care, and decision-making in underserved areas (Arefin, 2024), while digital health systems need strong policy support, privacy protection, interoperability, and stakeholder collaboration (Dileep, 2024).Last-mile technologies such as medical drones can improve medicine, vaccine, and diagnostic supply delivery, but health workforce capacity must also be strengthened (Ameso, 2024).Inclusive access models suggest that digital healthcare should be adaptable, community-centered, and designed for underserved populations(Abdul-Fattahi A Adetula, 2025). In Bangladesh, infrastructure, WASH, funding, governance, and trained workforce challenges may affect digital health implementation(Mohammad Ali & Tanzima Shahreen, 2024). In this study, ANN achieved the best performance with 99% accuracy, showing that machine learning can effectively classify the impact of digital health platforms in rural healthcare delivery.

6. Findings

1. The study found that digital health platforms can improve care coordination in rural healthcare delivery.
2. Key factors such as patient access, communication, service efficiency, and information sharing influenced the platform impact.
3. Machine learning models successfully classified the impact of digital health platforms into five categories.
4. Among the applied models, ANN performed best with 99% accuracy.
5. Digital health platforms can support better healthcare access, decision-making, and service integration in rural Bangladesh.

7. Recommendations

1. Rural healthcare systems should adopt digital health platforms to improve care coordination.
2. Communication between patients, community health workers, clinics, and hospitals should be strengthened through digital systems.
3. Machine learning models can be used to predict platform impact and support better decision-making.
4. Healthcare authorities should focus on improving patient access, referral systems, and service efficiency.
5. Further implementation of digital platforms can help reduce fragmentation in rural healthcare delivery.

8. Limitations

1. The study used a developed dataset, which may not fully represent all real rural healthcare conditions in Bangladesh.
2. The study focused only on selected healthcare service factors, while other social, economic, and infrastructure-related factors may also influence the platform impact.
3. Only four machine learning models were applied, so other advanced or hybrid models were not examined.

9. Conclusion

This study evaluated how a digital health platform can support coordinated care delivery in rural Bangladesh. The results show that digital platforms can improve healthcare access, communication, referral support, service coordination, and decision-making in fragmented rural healthcare systems.Among the four machine learning models, the ANN model achieved the best performance with 99% accuracy. This indicates that ANN can effectively predict the overall impact of digital health platforms across five impact categories: No impact, Low impact, Moderate impact, High impact, and Very high impact.

Therefore, this study concludes that machine learning-supported digital health platforms can help strengthen rural healthcare delivery in Bangladesh. Future studies should use larger real-world datasets from different rural areas to improve model reliability and practical application.

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