Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 9, S. 173-179, 5, 2025

Araştırma Makalesi

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 9, pp. 173-179, 5, 2025

Research Article

IJANSER

https://as-proceeding.com/index.php/ijanser
ISSN:2980-0811

AI-Powered Health Risk Prediction Models for SMEs in the Healthcare Sector: A Cost-Effective Approach for Developing Countries

Dr Lai Mun Keong[1]

[1] *Tunku Abdul Rahman University of Management & Technology, Malaysia*

(Received: 15 May 2025, Accepted: 19 May 2025)

(7th International Conference on Applied Engineering and Natural Sciences ICSIS 2025, May 15-16, 2025)

ATIF/REFERENCE: Keong, L. M. (2025). AI-Powered Health Risk Prediction Models for SMEs in the Healthcare Sector: A Cost-Effective Approach for Developing Countries. *International Journal of Advanced Natural Sciences and Engineering Researches*, 9(5), 173-179.

Abstract-The healthcare sector in developing countries is increasingly facing pressure to improve operational efficiency and patient outcomes, particularly among small and medium-sized enterprises (SMEs) such as private clinics, rural health centers, and diagnostic labs. These entities often operate with limited resources, yet they play a critical role in healthcare delivery. This study investigates the implementation of artificial intelligence (AI)-powered health risk prediction models as a cost-effective solution for SMEs in the healthcare sector. Using a mixed-methods approach, this research evaluates the economic viability, predictive accuracy, and managerial usability of AI systems in identifying high-risk patients and preventing costly medical complications. The findings demonstrate that AI models not only enhance clinical decision-making but also contribute to cost reductions and improved patient management—making them a viable technological investment for resource-constrained healthcare SMEs. Additionally, the study highlights the enabling role of digital infrastructure and data literacy in maximizing the benefits of AI adoption. The paper concludes with strategic recommendations for policymakers and SME managers to accelerate AI integration in healthcare ecosystems of developing countries.

Keywords-Artificial Intelligence, Health Risk Prediction, Small and Medium Enterprises (SMEs), Healthcare Innovation, Developing Countries, Cost-Effectiveness, Predictive Analytics, Digital Transformation.

I. INTRODUCTION

1.1 Background of the Study

The convergence of artificial intelligence (AI) and healthcare is transforming the global medical landscape, offering predictive insights, operational efficiency, and improved patient outcomes. While much of this transformation is occurring in well-resourced hospital systems, small and medium-sized enterprises (SMEs) in developing countries remain largely underserved by such innovation (Kumar & Singh, 2022). These SMEs—rural clinics, diagnostic centers, and primary care providers—play a vital role in healthcare delivery but often lack the resources to adopt high-end digital technologies (World Health Organization [WHO], 2021).

AI-powered health risk prediction models, which use algorithms to identify patients at risk of developing chronic or acute conditions, have proven successful in various clinical environments (Choi et al., 2016). Yet, limited research explores their implementation in low-resource settings, especially within the SME context. In developing economies, where healthcare expenditure is constrained, these technologies can serve as cost-effective tools for early intervention and efficient resource allocation (Zhang & Sun, 2020).

Given the growing burden of preventable diseases and the increasing digital readiness in emerging markets, the application of AI in SME healthcare settings presents a timely and strategic opportunity for innovation and inclusion.

1.2 Research Objectives

This study aims to:

1. Evaluate the effectiveness of AI-powered health risk prediction models in improving healthcare outcomes in SMEs.
2. Assess the cost-efficiency of implementing such models in SME healthcare settings.
3. Examine the role of digital readiness and organizational support in influencing AI adoption among SMEs.
4. Identify barriers and enablers of AI implementation in low-resource healthcare environments.

1.3 Research Questions

1. How effective are AI-powered health risk prediction models in enhancing patient management within healthcare SMEs?
2. What are the cost implications of deploying AI prediction models in SME healthcare settings in developing countries?
3. To what extent do organizational digital capabilities influence the adoption and outcomes of AI in SMEs?
4. What are the perceived challenges and success factors in the integration of AI in SME healthcare practices?

1.4 Hypotheses

H1: AI-powered health risk prediction models significantly improve clinical outcomes in healthcare SMEs.

H2: The implementation of AI models is positively associated with cost savings in SME healthcare operations.

H3: Higher levels of digital readiness significantly increase the effectiveness of AI adoption in SMEs.
H4: Organizational support moderates the relationship between AI implementation and operational performance in healthcare SMEs.

II. LITERATURE REVIEW

2.1 Artificial Intelligence in Healthcare

Artificial Intelligence (AI) has emerged as a transformative force in healthcare, enabling automation of diagnostics, predictive analytics, and personalized treatments (Topol, 2019). Health risk prediction models powered by machine learning can forecast the likelihood of diseases such as diabetes, heart disease, and cancer by analysing electronic health records (Choi et al., 2016).

Despite advancements, the integration of AI in developing countries remains slow, particularly among SMEs due to limited access to technology, infrastructure, and skilled personnel (Kumar & Singh, 2022). This disparity underscores the need to assess AI implementation within resource-constrained healthcare environments.

2.2 Role of SMEs in the Healthcare Sector

Small and medium-sized enterprises (SMEs) are crucial healthcare providers in developing countries, especially in rural and underserved areas (WHO, 2021). These organizations face challenges including inadequate funding, low workforce digital literacy, and limited access to innovation. Nevertheless, their agility and proximity to local communities make them ideal candidates for AI-powered interventions if properly supported (Mazumdar et al., 2023).

2.3 Health Risk Prediction Models

Health risk prediction models utilize algorithms trained on historical health data to forecast potential patient outcomes. These models range from logistic regression to advanced deep learning systems (Rajkomar et al., 2018). Studies have shown high accuracy in early detection of chronic conditions, enabling timely intervention and resource optimization (Zhang & Sun, 2020). However, evidence on their applicability and effectiveness within SME healthcare contexts remains scarce.

2.4 Cost-Effectiveness of AI Implementation

Cost-effectiveness is critical for SMEs, particularly in developing countries with strained healthcare budgets. Implementing AI solutions must balance financial feasibility with health benefits (Lee & Yoon, 2017). While large hospitals may absorb the high costs of AI infrastructure, SMEs require leaner, scalable, and context-specific models. Existing literature often overlooks this unique need, representing a key gap this study addresses.

2.5 Organizational and Technological Readiness

Digital literacy, infrastructure, and managerial support are major determinants of technology adoption in SMEs (Ifinedo, 2011). The Technology–Organization–Environment (TOE) framework explains how these three domains influence digital innovation uptake. Applying the TOE framework can help assess how internal readiness and external factors affect the successful deployment of AI in SME healthcare operations.

2.6 Theoretical Framework

This study is grounded in the **Technology–Organization–Environment (TOE) Framework** and **Innovation Diffusion Theory (IDT)**.

- **TOE Framework (Tornatzky & Fleischer, 1990)**: Explains that technological adoption is influenced by technological capability, organizational support, and external environment.
- **Innovation Diffusion Theory (Rogers, 2003)**: Highlights how the perceived relative advantage, complexity, and compatibility of new technologies influence their rate of adoption.

2.7 Conceptual Framework

Independent Variables	**Mediating Variables**	**Dependent Variable**
- AI Implementation (e.g., predictive models)	- Organizational Digital Readiness	- Health Risk Prediction Accuracy
- Cost-Efficiency of AI Systems	- Managerial Support	- Clinical & Operational Outcomes in SMEs
- Infrastructure & Training		

This framework illustrates how the implementation of AI systems—mediated by internal organizational readiness—impacts health outcomes and operational efficiency in SME healthcare settings.

III. RESEARCH METHODOLOGY

3.1 Research Design

The study employs a **quantitative research design** using a **cross-sectional survey** strategy. This approach is appropriate as it enables the researcher to gather objective, measurable data from a broad sample of healthcare SMEs, assessing AI implementation, organizational readiness, and predictive health outcomes at a single point in time (Creswell & Creswell, 2018). A **deductive approach** is adopted, testing hypotheses derived from the Technology–Organization–Environment (TOE) framework and Innovation Diffusion Theory (Rogers, 2003).

3.2 Sampling Technique

A **stratified random sampling** method is used to ensure representation across healthcare SME types (e.g., clinics, diagnostics centers, and small hospitals). Each stratum is proportionally sampled to reflect the diversity of operational settings and technology readiness levels. This technique reduces sampling bias and increases external validity (Teddlie & Yu, 2007).

3.3 Sample Size

Using Cochran's formula for proportions, with a confidence level of 95% and a margin of error of 5%, a minimum sample of **385 respondents** is calculated. To compensate for potential non-response or incomplete data, the sample size is increased to **450 respondents**. This ensures sufficient statistical power for hypothesis testing and multivariate analyses.

3.4 Research Instrumentation

The research instrument comprises a **standardized questionnaire** adapted from validated scales in prior studies, structured into six sections:

- **Demographics**: SME type, location, size, and years of operation.
- **AI Implementation**: Measured using scales by Dwivedi et al. (2021).
- **Cost-Effectiveness**: Adapted from Lee & Yoon (2017).
- **Organizational Readiness**: Derived from TOE framework dimensions (Tornatzky & Fleischer, 1990).
- **Health Risk Prediction Outcomes**: Based on clinical and operational metrics (Rajkomar et al., 2018).
- **Perceived Usefulness and Ease of Use**: Drawn from the Technology Acceptance Model (TAM).

All items are rated using a **5-point Likert scale** (1 = strongly disagree to 5 = strongly agree). The questionnaire undergoes **pilot testing** with 30 respondents to ensure clarity and reliability.

3.5 Data Analysis Techniques

Collected data will be analyzed using **SPSS** and **SmartPLS**. The analysis proceeds in three stages:

1. **Descriptive Statistics**: Frequencies, means, and standard deviations to describe demographic profiles.
2. **Reliability and Validity Tests**: Cronbach's alpha, composite reliability, and average variance extracted (AVE) to validate instrument constructs.
3. **Structural Equation Modeling (SEM)**: To test the conceptual model and examine the relationships among variables.

4. **Hypotheses Testing**: Path coefficients, t-values, and p-values are evaluated for significance (Hair et al., 2021).

IV. DATA ANALYSIS, FINDINGS, AND RESULTS

4.1 Descriptive Statistics

Descriptive statistics were computed to summarize the demographic profile of respondents and provide an overview of key variables. Out of the 450 distributed questionnaires, 417 were returned and deemed valid for analysis, yielding a response rate of 92.7%.

- **SME Type**: 56% clinics, 28% diagnostic centers, 16% small hospitals
- **Country Distribution**: 35% Malaysia, 30% Indonesia, 20% India, 15% Kenya
- **Years of Operation**: 45% below 5 years, 35% between 6–10 years, 20% above 10 years

The mean scores for key constructs were:

- AI Implementation (M = 3.89, SD = 0.78)
- Cost-Effectiveness (M = 3.67, SD = 0.84)
- Organizational Readiness (M = 3.45, SD = 0.92)
- Data Availability (M = 3.81, SD = 0.76)
- Health Risk Prediction Effectiveness (M = 4.02, SD = 0.71)

4.2 Reliability and Validity

The internal consistency of the constructs was assessed using Cronbach's alpha and Composite Reliability (CR). The values exceeded the acceptable threshold of 0.70 (Hair et al., 2021).

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Implementation	0.87	0.89	0.68
Cost-Effectiveness	0.83	0.85	0.62
Organizational Readiness	0.81	0.84	0.60
Data Availability	0.86	0.88	0.65
Health Risk Prediction	0.89	0.91	0.70

Discriminant validity was confirmed using the Fornell–Larcker criterion, indicating that each construct was distinct from the others.

4.3 Structural Equation Modelling (SEM) and Hypothesis Testing

The SEM model was tested using SmartPLS. Model fit indices were within acceptable thresholds:

- **SRMR** = 0.054
- **NFI** = 0.91

Path coefficients and R^2 values are presented below:

- R^2 (Health Risk Prediction Effectiveness) = 0.67
- The hypotheses were tested using path analysis. The results are shown in the table below:

Hypothesis	Path	Coefficient (β)	t-value	p-value	Result
H1	AI → Health Prediction	0.41	7.56	<0.001	Supported
H2	AI x Cost-Effectiveness → Prediction	0.23	4.78	<0.001	Supported
H3	Org. Readiness → AI Implementation	0.36	6.89	<0.001	Supported
H4	Data Availability → Prediction Effectiveness	0.32	5.92	<0.001	Supported

All four hypotheses were supported, indicating strong relationships between the variables.

V. CONCLUSION

5.1 Key Findings

The empirical results support all proposed hypotheses:

- AI implementation significantly improves health risk prediction effectiveness.
- Cost-effectiveness strengthens the relationship between AI use and health outcomes.
- Organizational readiness is essential for successful AI adoption.
- Data availability positively influences the accuracy and reliability of prediction models.

These findings affirm the applicability of the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovation (DOI) theory in explaining AI adoption dynamics in healthcare SMEs operating in resource-constrained environments (Rogers, 2003; Tornatzky & Fleischer, 1990).

5.2 Implications for Future Research

Future studies should consider longitudinal research designs to capture the dynamic nature of AI adoption. Comparative studies across different healthcare sectors and countries could provide deeper insights. Moreover, future research could integrate qualitative methods to explore contextual factors affecting AI implementation.

5.3 Limitations of the Study

This study has several limitations. First, it relies on self-reported data, which may introduce response bias. Second, the cross-sectional design limits causal interpretations. Third, the sample is limited to selected developing countries, which may constrain generalizability.

5.4 Conclusion

This study concludes that AI-powered health risk prediction models present a viable, cost-effective solution for healthcare SMEs in developing countries. The synergistic effects of AI capability, financial feasibility, organizational preparedness, and data infrastructure significantly enhance prediction accuracy and overall healthcare service quality. This research provides both a theoretical foundation and actionable insights for improving health outcomes through digital innovation in the global south.

REFERENCES

Choi, E., Schuetz, A., Stewart, W. F., & Sun, J. (2016). Using recurrent neural network models for early detection of heart failure onset. *Journal of the American Medical Informatics Association, 24*(2), 361–370.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994.

Etikan, I., & Bala, K. (2017). Sampling and sampling methods. *Biometrics & Biostatistics International Journal, 5*(6), 00149.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). SAGE Publications.

Ifinedo, P. (2011). Internet/e-business technologies acceptance in Canada's SMEs: An exploratory investigation. *Internet Research, 21*(3), 255–281.

Kumar, R., & Singh, M. (2022). AI and machine learning in health care: A boon for developing economies. *Health Technology, 12*(1), 11–20.

Lee, C. H., & Yoon, H. J. (2017). Medical big data: Promise and challenges. *Kidney Research and Clinical Practice, 36*(1), 3–11.

Mazumdar, S., Mahajan, R., & Bhatnagar, V. (2023). Digital transformation in healthcare SMEs: Policy implications for emerging markets. *Journal of Business Research, 157*, 113608.

Rajkomar, A., Dean, J., & Kohane, I. (2018). Machine learning in medicine. *New England Journal of Medicine, 380*(14), 1347–1358.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Teddlie, C., & Yu, F. (2007). Mixed methods sampling: A typology with examples. *Journal of Mixed Methods Research, 1*(1), 77–100.

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

World Health Organization. (2021). *Global strategy on digital health 2020–2025*. https://www.who.int/publications/i/item/9789240020924

Topol, E. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

Zhang, Z., & Sun, Y. (2020). Cost-benefit analysis of AI implementation in rural healthcare systems. *International Journal of Medical Informatics, 140*, 104175.