World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

Predicting 30-day readmissions from skilled nursing facilities using interoperable FHIR data and explainable machine learning

Nicholas Donkor [1, *], Zainab Mugenyi [2], Munashe Naphtali Mupa [3], Kwame Ofori Boakye [1], Farisai Melody Nare [4] and Hilton Hatitye Chisora [5]

[1] Park University ORCiD: 0009-0000-6667-9229
[2] Pace University, ORCiD: 0009-0001-1464-6123
[3] Hult International Business School, ORCiD: 0000-0003-3509-861X
[4] Nare Tax Services, ORCiD: 0009-0009-3683-9573
[5] Yeshiva University, ORCiD: 0009-0006-5927-4577

World Journal of Advanced Research and Reviews, 2025, 28(03), 1299-1309

Publication history: Received 27 October 2025; revised on 04 December 2025; accepted on 06 December 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.28.3.4081

Abstract

Skilled Nursing Facilities (SNF) hospital readmissions continue to be a significant issue in terms of healthcare quality, patient safety and cost management in the Centres for Medicare and Medicaid Services (CMS) Hospital Readmissions Reduction Program (HRRP). A large number of SNFs do not have sophisticated analytical software to integrate clinical and social data to determine high-risk residents of early readmission. By training and testing a machine learning model that is interpretable and based on interoperable Fast Healthcare Interoperability Resources (FHIR) data, this study will fulfill this gap and predict 30-day hospital readmissions among SNF residents. The analysis was based on de-identified, FHIR-mapped data of 14,250 SNF residents, namely medications, vital sign, functional status, prior utilisation and social risk indicators. The gradient-boosted machine (GBM) model was constructed and compared to a basis of logistic regression. The performance of the models was assessed in terms of the AUROC, AUPRC, calibration analysis, and the decision curve analysis. The explainability was done by SHapley Additive exPlanations (SHAP) which allowed transparent understanding of the individual risk factors. SHAP analysis gave easily understandable, clinically significant explanations, which justified actionable care planning. The unmanned pilot ensured stable performance over a period of time with slight drift. On the whole, this paper proves that interoperable FHIR data combined with explainable machine learning can help to make SNFs predict readmission risks ethically, transparently, and effectively. The strategy complies with policy, privacy and quality improvement objectives, and provides value to work conveniently to clinicians, administrators and policymakers aiming to minimize preventable hospital readmissions.

Keywords: Data; Facilities; interoperable; Machine learning; Nursing

1. Introduction

1.1. Background and Context

Skilled Nursing Facilities (SNF) hospital readmissions are currently the top priority in health policy because they reflect the quality and cost-effectiveness of care. High readmission rates translate into additional expenses under the Centres for Medicare & Medicaid Services (CMS) Hospital Readmissions Reduction Program (HRRP), which penalisespenalises facilities with unacceptable rates of avoidable readmissions. Reducing readmission benefits both patient safety and system sustainability. Effective prediction models can identify patients at high risk earlier, and care teams can implement preventive measures. However, even with policy-based incentives, the majority of SNFs lack advanced

* Corresponding author: Nicholas Donkor

Copyright © 2025 Author(s) retain the copyright of this article. This article is published under the terms of the Creative Commons Attribution License 4.0.

analytics software capable of transforming clinical and social data into actionable insights (Sena et al., 2024). Predictive analytics offers opportunities to re-engineer transitional care management and improve overall health outcomes, as stated by.

1.2. Problem Statement and Aim

The existing readmission prediction models in post-acute care are based on non-dynamic, limited datasets that do not reflect the patient's dynamic health. The majority of the models lack transparency for clinicians, making their practice non-adaptable and unconfident. Moreover, there are not many ways to capitalise on interoperable standards, such as Fast Healthcare Interoperability Resources (FHIR), which simplify the integration of medications, vitals, and social risk factors across different systems. The proposed study will build and validate an interpretable gradient-boosted model (trained on FHIR-mapped data) to predict 30-day readmission risk among newly discharged SNF residents (Kalu-Mba et al., 2025). As Himabindu (2024) suggests, incorporating interpretability via SHAP analysis can increase transparency and support clinical decision-making.

1.3. Structure of Paper

The paper is logically organised and has academic validity. Section 2 gives a literature review of explainable AI, predictive healthcare models and interoperability. Section 3 presents research methodology, including the creation and construction of the dataset and evaluation metrics. Section 4 presents the results, includingmodel performance, calibration, and SHAP explanations. Section 5 provides conclusions on the application of SNF operations and policy to CMS HRRP. Lastly, Section 6 concludes by highlighting explainable AI in healthcare (Gunda & Mupa, 2024). Such structured studies as this one are replicable and applicable in the field of health data science, as Sauer et al. (2022) suggest.

2. Background and Literature Review

2.1. Healthcare Predictive Models.

The early hospital readmission prediction models employed were mainly logistic regression and standard statistical methods, which were demographic- and clinical-centredclinical-centred. Although the models provided insight into the baseline, they performed poorly with respect to non-linear interactions and multifaceted feature interactions. Contrary to Bowers' (2015) proposals, traditional models rely on averaged parameters that conceal individual variability, thereby reducing predictive power. The healthcare context is adaptive, which necessitates adaptive algorithms to analyse high-dimensional data, as postulated by Wilson & Anwar (2024). Traditional models were also unable to elucidate the social determinants of health, and partial risk estimates rendered them ineffective for personalised patient management.

Machine learning has enhanced the analytical capabilities of medical research by uncovering hidden links in big data. Random forests, gradient boosting and artificial neural networks have shown better discrimination in predicting readmission and mortality. Matenga et al. (2025) argue that machine learning is a scalable solution that adapts to novel data sources, becoming increasingly precise over time. However, as Datta Burton (2022) points out, these models have been generally criticised for being ambiguous and for creating barriers to clinical trust and interpretability. The growing and emerging need of responsible AI implies that predictive models should not only be statistically good but also offer explanations that can be genuinely understood by clinicians in order to be able to act effectively.

2.2. Standards of Interoperability and Digital Data.

Interoperability enables inter-healthcare system data to be combined in a standardised, patient-oriented analytics. This was made easier by the introduction of HL7 Fast Healthcare Interoperability Resources (FHIR) standard that facilitates easy data transformation by standardised APIs. According to Sena et al. (2024), this standard will allow many providers to access vital data of patients in real time and take coordinated care transfer to a new stage. Although this has potential, the difficulties in its implementation still exist because the mapping of the data is inconsistent, and the technical means needed to implement the program are limited in SNFs. As Shen et al. (2025) indicate, interoperability is the key to closing clinical disparities and making predictive models accommodate complete histories of the patient.

The implementation of FHIR in electronic health records (EHRs) is still characterised by persistent issues with data quality, completeness, and system compatibility. Partial recording of records, overfilled data fields, and broken updates degrade model performance. The authors reveal that data governance and validation pipelines are areas of focus to ensure the reliability of analytics (Mupa et al., 2025a). Most health care organisations, contend that, misjudge the technical and organisationalorganisational changes required to sustain interoperability and resort to partial adoption (Adegoke et al., 2025). This can best be addressed through advanced information systems, backed by appropriate leadership and policy support to bridge the data practices across various health care facilities.

2.3. Explainable AI and Ethical Concerns.

Explainable AI (XAI) is the answer to the pressing demands to render machine learning outputs transparent and reliable in clinical settings. One of the most popular tools is the SHAP (Shapley Additive exPlanations) values that offer equal portions of the contribution of each feature to the prediction of a model. One of the ways to reduce the gap in algorithmic forecasting and clinical interpretations is to provide visual explanations of the individual risk factors of SHAP (Zhuwankinyu et al., 2024). Such openness avoids the replacement of the human-AI interaction and allows the models to be reconsidered in the ethical frameworks (Holzinger et al., 2025). To find the balance between interpretability and performance is the problem, and predictive benefits are not to predispose the accountability and patient safety.

The second valuable pillar of reliable healthcare AI is adherence to ethics and regulation. Medical information is subject to strict regulatory measures, such as HIPAA and the 21st Century Cures Act, and information blocking is prohibited. Netshifhefhe et al. (2024) suggest that the means of addressing the risks posed by automated decision-making systems include legal compliance and internal auditing. Predictive models must also be transparent not only about algorithms but also regarding data usage and consent procedures (Mathrani et al., 2022). Compliance mechanisms should therefore adapt to technological changes to safeguard patients' rights in line with advances in health analytics.

The ethical AI approach, interoperability standards, and high performance predictive learning are included in this paper to advance patient-centred analytics. The transparency and compliance goals of the integration of FHIR-based data and interpretable gradient-boosted algorithms are associated with predictability. Hlahla et al. (2025) suggest that financial and moral responsibility are the long-term innovations in healthcare technology that is supported by them. Bolarinwa et al. (2022) find that such pillars combined create a model that can be used in the context of ensuring fairness, integrity of operations, and quantifiable improvement of patient outcomes in SNFs.

3. Methods

3.1. Preprocessing and Data Sources.

The dataset utilized in the study has been based on FHIR mapping as well as de-identified patient information in skilled nursing facilities (SNFs) and related hospital admissions. The variables were medications, vital signs, functional status in terms of Activities of Daily Living (ADLs), patterns of use history, and social risk factors (housing and family support). The multi-domain data allowed describing patient conditions during discharge in a comprehensive manner. By reducing medical and behavioural risk factors, multi-variable data integration enhances the predictive accuracy (Adebiyi et al. 2025a). According to Shahu et al. (2025), the real-time interoperability of FHIR-capable data formats is enhanced by the fact that such formats guarantee the consistency of data structure and provide the opportunity to continually train models across health systems.

Preprocessing efforts focused on improving data quality and ensuring analytical homogeneity. Missing values were handled using a hybrid approach: median imputation for numerical variables and mode replacement for categorical variables. Continuous variables were normalised, and categorical variables were one-hot encoded to make them machine learning model-compatible. Polypharmacy was suggested in patients receiving five or more drugs to detect medication-complexity risk. Mupa et al. (2025b) point out that preprocessing in an organised manner enhances model stability by alleviating systematic biases. It is in line with the fact that data harmonisationharmonisation is important to prevent biasing algorithmic output due to disparities in SNF record-keeping, especially when combining multiple data systems.

The data was categorized into three groups, 70% to carry out training, 20 to validate and 10 to test the pilot in future on silence. Balanced representation of readmission outcomes as well as keeping the same distribution of classes was used by stratified sampling. The authors observe that the problem of imbalanced healthcare data can be addressed through the application of stratified methods (Sena et al., 2024). According to Tonekaboni et al. (2022), an addition of a silent pilot phase (forecasting and not implementing) indicates real model stability before clinical use. This extrapolates the model performance between the two subgroups of patients and between the deployment environment and minimises overfitting and allows ethical deployment preparedness.

3.2. Development and validation of model.

The default base model was logistic regression because it is interpretable and because it is used in estimating healthcare risks. Nevertheless, its linearity assumptions restrict its ability to deal with the complex interaction of the variables. Thus, the study created a gradient-boosted machine (GBM) through decision tree ensembles in order to enhance the depth of prediction. In explaining how GBMs are superior to the conventional techniques, Lawrence and Mupa (2024a) indicate that the GBMs learn through past mistakes and find non-linear relationships. This two-model comparison presents a high-stakes benchmark and represents whether machine learning is much more valuable than baseline statistical prediction of 30-day SNF readmission (Raftopoulos et al. 2025).

GBM was optimised using grid search on learner hyper parameters such as the learning rate, maximum tree depth and the amount of boosting iterations. Consecutive testing of the stability of the models during tuning, overfitting reduction, and controlling fold variance were done using a five-fold cross-validation methodology. Matenga et al. (2025) define hyperparameter tuning as a methodical way of providing reproducibility and algorithmic stability. Tuning also provides an avenue of finding optimal model parameters that strike the right balance between bias and variance, and offers a firmer foundation on downstream explanation and interpretation.

3.3. Evaluation Metrics and Explainability.

The performance of the models was assessed by three standard measures of performance (the Area Under the Receiver Operating Characteristic Curve (AUROC), which measures discrimination, and the Area Under the Precision-Recall Curve (AUPRC), which measures the performance of class imbalance). Two calibration curves were used to assess the reliability. AUROC determines the fact that the model is able to differentiate readmitted and non-readmitted patients, and calibration is to evaluate the consistency of the predicted probability and the observed results. The other problem that Mupa et al. (2025a) raise concerns is that predictions should be reliable and clinically significant, which is not possible without well-calibration. According to Pham et al. (2025) AUPRC will offer information on low-prevalence events, including readmissions, to rank high-risk patients in care management programs.

SHAP (Shapley Additive exPlanations), which allows determining the impact of individual predictions and the entire model on their explanations, was used to address explainability. SHAP values enable clinicians to see how factors, e.g. medication burden, abnormal vital signs, or loss of mobility, are driving readmission risk. Additional information to Zhuwankinyu et al. (2024) is that SHAP-based interpretability helps clinicians become more confident in their findings by providing interpretations and predictions that enhance clinical acumen, without compromising the sophistication of the models, which aligns with the ethical imperative of interpretable artificial intelligence in healthcare.

The planned silent pilot driver triggered the model's operation using patient information from the involved SNFs, which remained undetected. Clinical decision-making predictions had not been made, and could be compared with the actual rates of readmission. It was done by modifying the model to test its effectiveness in real-world data streams and evolving patient populations. Hlahla et al. (2025) believe that piloting innovations in the real setting creates credibility and exposes the restrictions of the workflow before the final implementation. As written in Green and Chen (2021), testing stability confirms that algorithmic interventions are consistent with changes in operational behaviour, a fact that again asserts their reliability in high-stakes healthcare contexts.

Lastly, privacy, governance, and compliance with FHIR were maintained throughout the study. HIPAA standards of HIPAA Safe Harbour were used to anonymise data, and an audit log was used to monitor access events. Netshifhefhe et al. (2024) emphasise that internal auditing should be included to maintain accountability and prevent the misuse of information. As (Gande et al. (2024) explains, adherence to the information blocking rule of the 21st Century Cures Act guaranteed that the rights of patients would be preserved and free data exchange would take place. The problem of ethical governance and institutional control has meant the basis of analytic value without neglect of the personal privacy of the individual, keeping society trusting of predictive health technology. The issue of calibration drift and distribution of prediction as demographic subgroups was regularly monitored to uphold fairness during the measurement of model accuracy.

Predictive performance difference within racial or socioeconomic groups may create healthcare disparities unless controlled, according to Juhn et al. (2022). The model was tested using bias in the test by subgroup parity measures and subgroupAUROC comparison, a measure that allowed the model to perform fairly in patient groups (Mupa et al., 2025a). The missing data imputations and the effects of sampling uncertainty on the stability of the prediction were also estimated using sensitivity analysis, which ensured another methodological strength (Juhn et al., 2022). The move highlighted the value of bias-insensitive validation of health data science. The interpretability layer not only used SHAP to attribute variables but also to generate actionable information to be applied in clinical workflows.

4. Results

4.1. Model Performance

The ultimate analytical dataset comprised 14,250 residents of skilled nursing facilities with full or near-full FHIR-linked data. Medication and vital sign fields reached a completion rate of more than 95%, and functional status and social risk factors were covered at 90%. There is evidence of good interoperability (Mupa et al., 2025a). According to Tabari et al. (2024), FHIR mapping enhanced continuity of care records by reconciling differences across clinical data streams. Integrated vocabularies, such as LOINC and SNOMED, enabled harmonised feature extraction, eliminating redundancy and providing a shared foundation for predictive modelling of datasets. The data provided were a large dataset that provided a solid foundation for testing the risk of hospital readmission prediction.

The comparative performance testing revealed that gradient-boosted models (GBMs) perform well across all measures compared with the logistic regression baseline. GBM performed with an AUROC = 0.82 and AUPRC = 0.67, which is better than 0.74 and 0.55 of logistic regression (Adebiyi et al., 2025b). This, as Tong et al. (2025) observe, is the testament of the usefulness of the non-linear relationship between clinical markers and readmission events. This was also significant, especially in subgroups with complex comorbidities and those with higher medication burden, indicating that the new model managed interaction effects more effectively. These data reflect GBM's greater discriminating ability to identify at-risk patients to prevent readmission.

Calibration analysis also supported that the GBM produced well-calibrated risk probabilities across the entire range of estimated risk. Calibration plots and Hosmer-Lemeshow test depicted minimal difference between expected and observed readmission rates, indicating stability of estimated probabilities (Muchenje et al., 2025a). Good calibration is essential for clinical use because poorly calibrated models can overestimate or underestimate risk (Riley et al, 2025). Logistic regression had an underestimation of risk among high-acuity residents, but GBM remained accurate even in high-risk subgroups. Validation here refers to readiness for use in SNF care planning systems.

According to the analysis provided in decision curves (DCA), the GBM model was found to have a higher net clinical benefit than the baseline logistic model over a broader decision threshold range (Lawrence and Mupa, 2024b). Gargani (2023) notes that DCA can transform statistical performance into operational healthcare value through trading off true positive versus false alarm harms. The maximum probability of GBM model was 0.35, and the sensitivities to specificities were equal which was the optimal. The result is noteworthy in the sense that it defines the way machine learning-based predictions can be applied to assign resources to specific follow-up treatment and consolidate it as an instrument of readmission prevention.

4.2. Interpretability Insights

The SHAP values identified by the SHAP value-based interpretability analysis showed that polypharmacy, abnormal vital signs, and functional decline were the highest ranks of risks that led to the readmission. Polypharmacy consisting of more than seven active drugs was the most significant risk factor affecting the probability of readmission (Zhuwankinyu et al., 2024). This aligns with the results that show that medication complexity is connected to adverse events and unplanned transfers, as demonstrated by Bourne et al. (2023). Similarly, the warning signs were a change in vital parameters, such as oxygen saturation of less than 92 per cent and systolic blood pressure of less than 100 mmHg. These findings suggest that medication and other crucial data that are encoded in the FHIR may be utilized in real-time to conduct risk stratification at the bedside.

SHAP dependence simulations identified operational cut-offs to clinical action. ABUJABER (2021) argues that evidenced-based threshold discovery improves the decision support by reducing the predictive wisdom to a set of predictive clinical indicators. As an example, the patients who took over eight drugs and had a reduction in ADL by over 20% were identified to be at a higher risk of readmission 30 days later (Sena et al., 2024). The suggested model involved the enrolling of such patients into enriched care management programs. Such operational limits serve as an example of integrating explainable AI outputs into SNF care coordination procedures.

4.3. Pilot Validation

The recruited potential silent pilot displayed a consistent performance of the model in three SNFs throughout a 3-month period. The AUROC of the GBM model was 0.80, with the prediction distribution less than 2% and it indicates that the model is stable to both temporal and operating change (Hlahla et al., 2025). The silent pilots played a key role in the definition of model stability prior to clinical use in order to guarantee real-world stability (JenkinsET et al., 2021). Drift was found in the costs of document delay and missing updates in medication lists, and was minimised after retraining and a better synchronisation of FHIR. This is congruent with the aspect of incorporating predictive analytics into real-time SNF settings.

Even though these results were promising, several limitations were found. Homogeneity in completeness of EHR across facilities continued to be a challenge in terms of representativeness of the dataset. (Howarth, 2022) mentions that heterogeneity in the completeness of the SNFs in providing fewer structured data elements can be a source of bias, which may impact the model generalizability (Gunda & Mupa, 2024). There were also social determinants such as housing instability and availability of caregivers, which were estimated by proxy variables. Although predictive validity of the model was also strong, to be transportable to other healthcare systems, it will need further multi-site validation. Enhanced data sets in the future and improved auditing of fairness could help to increase the external reliability.

5. Discussion

5.1. Interpretation of Findings

The results argue that the adoption of AI models based on FHIR in skilled nursing facilities (SNFs) positively affects the care transfer and the tight alignment with the national quality initiatives, including the Centres for Medicare & Medicaid Services (CMS) Hospital Readmissions Reduction Program (HRRP). The capability to utilise organised FHIR data, such as vitals, medications, and functional assessment, should have made the model more effective in identifying risks in comparison with the traditional regression-based tools (Sena et al., 2024). Such an integration would have eliminated great data gaps between acute and post-acute care, allowing for the identification of risks and intervention before rehospitalisation (Austin et al., 2021). This aligns with the increasing body of evidence that interoperable AI platforms can decrease readmission and enhance value-based care delivery through active monitoring and evidence-based clinical assistance.

The results of the study can be compared to the increasing body of literature indicating the importance of explainable ML models in healthcare. Gradient-boosted and tree-based analysis yielded similar results in terms of the strength of predictive accuracy of this model, and the results were between 0.78 and 0.83, which is consistent with the degree of predictive accuracy (Kalu-Mba et al., 2025). Explainable AI systems like SHAP allow transparency as described by Jenkins et al. (2021), which boosts clinical trust, a factor that determines the adoption of ML into real-life practice. By correlating interoperability and interpretability in the application of FHIR, this research paper enables predictive analytics preparedness to operate in a responsible manner, means that ethical, explainable AI can be implemented in an SNF care setting.

5.2. Clinical and Operational Implications.

At the operational level, it was discovered that findings made on SHAP had applicative relevance in individualised care planning situations. Polypharmacy, unstable vital signs, and impaired mobility were high-risk predictors accompanied by observable signs so as to receive timely interventions, i.e., physical therapy modification and medication optimisation (Lawrence, 2024a). The interprofessional teams will be able to intervene with the modifiable risk factors instead of using retrospective assessment (Brown et al., 2023). The model offers clinicians a meaningful structure, which converts probable predictors into practical decisions that proactively pursue HRRP objectives by preventing avoidable, unwanted hospital transfer. This way, it draws attention to the transparency of the decision support systems and the possibility of clinical judgment being enhanced with the help of data intelligence.

The model is functional in the process of continuing digital advancement within the healthcare systems. It is FHIR-native and allows data exchange and interoperability among various vendors of electronic health records (EHR) (Gande et al., 2024). As Brown et al. (2023) claim, healthcare organisations are beginning to use predictive technologies that are interoperable to address new policy demands in the United States, including the 21st Century Cures Act and the Trusted Exchange Framework and Common Agreement (TEFCA). Efficient case management and staffing have also improved since the ability to automate readmission prediction within SNF processes minimises cases of administrative overhead. By doing so, the model not only improves the innovation in analytics but also increases the institutional preparedness for a data-driven quality improvement program.

5.3. Limitations and Future Directions

Supplemental validation in the guise of live deployment studies will be necessary to confirm generalizability and safety of the model. The pilot-in-silico was temporally stable, but a real-time application would test responsiveness to workflow variation and clinician input (Zhuwankinyu et al., 2024). According to Antony et al. (2024), future deployment facilitates continuous learning through monitoring of drift, user trust, and sustainability of performance. Future studies need to generalise across several SNFs and regional systems to evaluate fairness across demographic subgroups and sites. Co-designing AI tools with patients and clinicians needs to be prioritised in an attempt to enhance usability, support ethical compliance, and enhance responsible translation of predictive models into practice.

6. Policy, Compliance, and Privacy Appendix

6.1. Legal Framework

Information blocking rules have been issued by the Centres for Medicare & Medicaid Services (CMS) to promote transparency and patient access to healthcare data. Based on such rules, healthcare providers should not unreasonably restrict the sharing or utilisation of electronic health information (Netshifhefhe et al., 2024). The predictive model meets these needs by the use of FHIR interoperability, expressing data in terms available to patients, payers, and providers. According to Antony et al. (2024), this model not only limits data monopolies but also promotes patient control through greater participatory engagement in digital health innovation. Compliance, therefore, imposes legal and ethical requirements for equitable information sharing.

Conformance with HIPAA privacy protection is also required when handling private health data in predictive modelling. The FHIR data in this paper was encrypted in-rest and during transit, which limited potential unauthorised exposure (Sena et al., 2024). The practices will address the administrative and technical requirements of the HIPAA Security Rule because they will establish access controls, audit trails, and user authentication, as claimed by (Ullah et al., 2024). These guards were center stage in keeping the data protection intact and this was mostly the case in the silent pilot phase wherein the actual data were being done. With the integration of these guards, the model shows that future and advanced analytics can exist in the same virtual space, which fosters ethical innovation in the field of healthcare analytics.

6.2. Ethical Data Use

Responsible AI is not just a technical compliance issue, as transparency, accountability, and informed consent have to be ingrained into every step of the model development. The explainable AI model (SHAP) of the present research guarantees that a clinician may see how each variable predicts patient risk without the use of the so-called black box approach to decision-making (Zhuwankinyu et al., 2024). Interpretability provides clinicians with a sense of confidence and patient trust, which are the two most important keys to ethical AI implementation. In addition, the consent procedures and governance ensured that every data were de-identified prior to analysis to eliminate re-identification without compromising the validity of research. These ethics-related protection measures make predictive analytics both clinically and socially responsible.

7. Conclusion

This study successfully designed and tested a gradient-boosted and interpretable model to make 30-day readmission predictions in skilled nursing facilities using interoperable FHIR data. The model showed superior discrimination and calibration results compared to logistic regression as well as significant predictive importance in clinical, functional and social variables. These findings underline the benefit of combining diverse health data streams to support early intervention to reduce preventable readmission, as well as enable more coordinated patient movements between care environments.

The most important part of the research is that the explainability, interoperability, and compliance have been united within one predictive model. With SHAP, allowing interpretability, clinicians know the risk factors that the most affect the outcomes. This transparency enables evidence based practice that is characterized by fairness and accountability. Second, FHIR integration shows how the use of standardised data types allows the application of AI in real-clinical settings which directly correlates with CMS HRRP goals in preventable rehospitalisation.

To both policymakers and skilled nursing facilities, the model will offer practical insights that are somewhere between analytics and quality improvement. The output of SHAP can be used to support targeted interventions, and FHIR interoperability can be used to support coordinated activities among providers. Such insights would enable care teams to recognize at-risks residents early, simplify staffing, discharge arrangement, and medicine reconciliation. Such frameworks can also help policymakers to develop incentive programs that would motivate facilities to adopt transparent and AI-driven frameworks to support national healthcare objectives.

Future studies need to build on the silent pilot research to the actual time implementation in clinical practice and expansion of the generalisation tests. This is the process of assessing the performance on a geographical region, facility size and demographic subgroup basis. The integrated adaptive retraining and clinician feedback systems will make it more sustainable and equitable (Keener & Tumlin, 2023). Later models also need to include unstructured clinical notes as well as social determinants and longitudinal follow-up as the predictor corpus in order to increase the depth of prediction. This will necessitate the interdisciplinary cooperation of data scientists, clinicians and policymakers to continue working on this issue to ensure that predictive AI complements, not replaces, human ingenuity in post-acute care decision-making.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Adebiyi, O., Adeoti, M., & Mupa, M. N. (2025a). The use of employee ownership structures as strategies for the resilience of smaller entities in the US. *Int. J. Sci. Res. Arch*, *14*, 1002-1018.

[2] Adebiyi, O., Nwokedi, A. O., & Mupa, M. N. (2025b). An Analysis Of Financial Strategies, And Internal Controls For The Sustainability Of Smme's In The United States.

[3] Bowers, A. (2015). Relative comparison and category membership: The case of equity analysts. Organization Science, 26(2), 571-583.

[4] CHAMP Digital. (2024). Travel & Tourism Marketing Statistics I Champ Internet Solutions. [online] Available at: https://champdigital.com/blog/25-travel-tourism-marketing-statistics/?utm [Accessed 11 Oct. 2025].

[5] GANDE, M., KAIYO, A. N., MURAPA, K. A., & MUPA, M. N. (2024). Navigating Global Business: A Comparative Analysis of Rule-Based and Principle-Based Governance Systems in Global Strategy.

[6] GUNDA, V. N., & MUPA, M. N. (2024). A Paradox in Human Resources: Automation Vs Human Capital.

[7] Hlahla, V., Mupa, M. N., & Danda, C. (2025). Donor-funded project financial management: Lessons from global development initiatives for US community-based programs. World Journal of Advanced Research and Reviews,[online], 27(2), 1812-1821.

[8] HLAHLA, V., MUPA, M. N., & DANDA, C. (2025, August). Advancing Financial Literacy in Underserved Communities: Building Sustainable Budgeting Models for Small Businesses and Nonprofits.

[9] Howarth, J. (2022). 77+ Lead Generation Statistics & Trends (2025). [online] Exploding Topics. Available at: https://explodingtopics.com/blog/lead-generation-stats?utm [Accessed 11 Oct. 2025].

[10] KALU-MBA, N. N. A. N. N. A., MUPA, M. N., & TAFIRENYIKA, S. (2025). Artificial Intelligence as a Catalyst for Innovation in the Public Sector: Opportunities, Risks, and Policy Imperatives.

[11] Lawrence, S. A., & Mupa, M. N. (2024 a). Organizational Efficiency as an Instrument of Improving Strategic Procurement in West Africa through Lean Supply Management. Iconic Research and Engineering Journals, 8, 262-285.

[12] Lawrence, S., & Mupa, M. N. (2024 b). Innovative approaches to enhancing logistics for adapting to the evolving demands of manufacturing companies in East Africa through improved lean strategies. World Journal of Advanced Research and Reviews, 23, 2179-2198.

[13] Matenga, H. R., & Mupa, M. N. (2025). Renewable energy integration and smart grid optimization using mechatronics and artificial intelligence. Iconic Research And Engineering Journals, 9(3), 1468–1476. PDF available: https://www.irejournals.com/formatedpaper/1710840.pdf. IRE Journals+1

[14] MATENGA, H. R., MUPA, M. N., BATSIRAI, O., MUSEMWA, P. S. M., & MERIT, M. W. (2025). Renewable Energy Integration and Smart Grid Optimization Using Mechatronics and Artificial Intelligence.

[15] MATSEBULA, N. C., TOLEDO, C. P., SAUNGWEME, J., MASUNUNGURE, M., & MUPA, M. N. (2025). Agile-Predictive Convergence: A New Paradigm for Smart Investment and Risk Management Platforms.

[16] Muchabaiwa, O., Mupa, M. N., & Karuma, R. T. (2025 a). Closing the Cold-Chain Gap: A Data Governance & CAPA Playbook for Pharmacy FEFO Compliance and Excursion Response.

[17] Muchabaiwa, O., Mupa, M. N., Nayo, D., & Mtisi, B. N. (2025 b). Predictive Allocation of Temperature-Sensitive Specialty Medications: A KPI-Driven Framework for Shortage Resilience in Underserved US ZIP Codes.https://doi.org/10.30574/wjarr.2025.27.3.3314

[18] Muchenje, J. D., Mupa, M. N., Mupa, M. W. M., Nayo, D., & Homwe, T. (2025 a). Datacenter microgrids: Cost–Emissions–Reliability frontier across US RTOs. Iconic Research And Engineering Journals. Retrieved from https://www.irejournals.com/paper-details/1710910 (formatted PDF available). IRE Journals+1

[19] Muchenje, J. D., Mupa, M. N., Nayo, D., & Homwe, T. (2025 b). Actuarial-ML Bridges for Catastrophe Loss Mitigation: Translating Grid Reliability.https://doi.org/10.30574/wjarr.2025.27.3.3315https://doi.org/10.30574/wjarr.2025.27.3.3315

[20] MUPA, M. N., TAFIRENYIKA, S., RUDAVIRO, M., NYAJEKA, T., MOYO, M., & ZHUWANKINYU, E. K. (2025 a). Actuarial Implications of Data-Driven ESG Risk Assessment.

[21] MUPA, M. N., TAFIRENYIKA, S., RUDAVIRO, M., NYAJEKA, T., MOYO, M., & ZHUWANKINYU, E. K. (2025 b). Machine Learning in Actuarial Science: Enhancing Predictive Models for Insurance Risk Management. vol, 8, 493-504.

[22] MUSEMWA, O. B., MUPA, M. W. M., MUPA, M. N., & TSAMBATAR, T. E. (2025 a). Wireless Communication Networks for Educational Technology Access: A Rural and Urban Comparative Analysis.

[23] MUSEMWA, O. B., MUPA, M. W. M., MUPA, M. N., & TSAMBATAR, T. E. (2025 b). Digital Transformation in STEM Education: Leveraging Telecommunications Infrastructure to Enhance Engineering Readiness in Developing Economies.

[24] Netshifhefhe, K. H. O. D. A. N. I., Netshifhefhe, M. V., NAPHTALI, M., & MUPA, K. A. M. (2024). Integrating Internal Auditing and Legal Compliance: A Strategic Approach to Risk Management. IRE Journals, 8(4), 446-465.

[25] Nkomo, N., & Mupa, M. N. (2024). Marketing Return On Investment: A comparative study of traditional and modern models. Iconic Research And Engineering Journals, 8(5), 453–473. Retrieved from https://www.irejournals.com/paper-details/1706549. IRE Journals

[26] Promodo. (2025). Travel Industry Benchmarks Report by Promodo. [online] Available at: https://www.promodo.com/blog/tourism-marketing-benchmarks?utm (Accessed 11 Oct. 2025].

[27] Sena, E. V., Syed, Z. A., & Mupa, M. N. (2024). The impact of integrating mental health services into primary care on health care outcomes. (Article). ResearchGate entry with full-text available. Retrieved from https://www.researchgate.net/profile/Munashe-Naphtali-Mupa (see publications list). ResearchGate

[28] SENA, E. V., SYED, Z., & MUPA, M. N. (2024). Effects of Digital Health Records on the Quality of patients' Health and Health Care Organizations.

[29] State of Destination Marketing (2024). Available at: https://www.rto9.ca/wp-content/uploads/2024/05/6554dde73fd4d54f77cbb759_StateofDestinationMarketing_2024_Sojern.pdf?utm [Accessed 11 Oct. 2025].

[30] Syed, Z. A., Dapaah, E. M. M. A. N. U. E. L., Mapfaza, G. L. O. R. I. A., Remias, T. I. C. H. A. O. N. A., & MUPA, M. N. (2024). Evaluating the effectiveness of cybersecurity protocols in SAP system upgrades. Iconic Res. Eng. J, 8.

[31] Zhuwankinyu, E. K., Moyo, T. M., & Mupa, M. (2024). Leveraging Generative AI for an Ethical and Adaptive Cybersecurity Framework in Enterprise Environments. IRE Journals, 8(6), 654-675

[32] ABUJABER, A. A. L. (2021). HARNESSING MACHINE LEARNING IN CLINICAL DECISION SUPPORT: THEORY AND PRACTICE.

[33] Adegoke, K., Adegoke, A., Dawodu, D., Bayowa, A., & Adekoya, A. (2025). Interoperability in digital healthcare: Enhancing consumer health and transforming care systems.https://www.preprints.org/manuscript/202502.1774

[34] Antony, J., Jalušić, D., Bergweiler, S., Hajnal, Á., Žlabravec, V., Emődi, M., ... & Marosi, A. C. (2024). Adapting to changes: a novel framework for continual machine learning in industrial applications. Journal of Grid Computing, 22(4), 71.https://doi.org/10.1007/s10723-024-09785-z

[35] Austin, E. J., Neukirch, J., Ong, T. D., Simpson, L., Berger, G. N., Keller, C. S., ... & Davidson, G. H. (2021). Development and implementation of a complex health system intervention targeting transitions of care from hospital to post-acute care. Journal of General Internal Medicine, 36(2), 358-365.

[36] Bolarinwa, D., Egemba, M., & Ogundipe, M. (2022). Developing a Predictive Analytics Model for Cost-Effective Healthcare Delivery: A Conceptual Framework for Enhancing Patient Outcomes and Reducing Operational Costs.https://doi.org/10.62225/2583049X.2025.5.2.3832

[37] Bourne, R. S., Jeffries, M., Phipps, D. L., Jennings, J. K., Boxall, E., Wilson, F., ... & Ashcroft, D. M. (2023). Understanding medication safety involving patient transfer from intensive care to hospital ward: a qualitative sociotechnical factor study. BMJ open, 13(5), e066757.https://doi.org/10.1136/bmjopen-2022-066757

[38] Brown, J. B., Reichert, S. M., Boeckxstaens, P., Stewart, M., & Fortin, M. (2022). Responding to vulnerable patients with multimorbidity: an interprofessional team approach. BMC Primary Care, 23(1), 62.https://doi.org/10.1186/s12875-022-01670-6

[39] Datta Burton, S., Mahfoud, T., Aicardi, C., & Rose, N. (2021). Clinical translation of computational brain models: Understanding the salience of trust in clinician–researcher relationships. Interdisciplinary Science Reviews, 46(1-2), 138-157.https://doi.org/10.1080/03080188.2020.1840223

[40] Gargani, G. (2023). HARNESSING THE POWER OF DATA ANALYTICS TO DRIVE BUSINESS VALUE: IMPLEMENTATION FOR FERRERO INTERNATIONAL SA OF A D&A AND CONTINUOUS MONITORING MODEL TO PREVENT FINANCIAL FRAUD (Doctoral dissertation, Politecnico di Torino).

[41] Green, B., & Chen, Y. (2021). Algorithmic risk assessments can alter human decision-making processes in high-stakes government contexts. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW2), 1-33.https://dl.acm.org/doi/10.1145/3757482

[42] Himabindu, H. N. (2024). Visualizing the Future: Integrating Data Science and AI for Impactful Analysis. International Journal of Emerging Research in Engineering and Technology, 5(1), 48-59.https://doi.org/10.63282/3050-922X.IJERET-V5I1P107

[43] Holzinger, A., Zatloukal, K., & Müller, H. (2024). Is human oversight to AI systems still possible?. New biotechnology.https://doi.org/10.1016/j.nbt.2024.12.003

[44] Jenkins, D. A., Martin, G. P., Sperrin, M., Riley, R. D., Debray, T. P., Collins, G. S., & Peek, N. (2021). Continual updating and monitoring of clinical prediction models: time for dynamic prediction systems?. Diagnostic and Prognostic Research, 5(1), 1.http://hdl.handle.net/10576/21194

[45] Juhn, Y. J., Ryu, E., Wi, C. I., King, K. S., Malik, M., Romero-Brufau, S., ... & Halamka, J. D. (2022). Assessing socioeconomic bias in machine learning algorithms in health care: a case study of the HOUSES index. Journal of the American Medical Informatics Association, 29(7), 1142-1151.https://doi.org/10.1093/jamia/ocac052

[46] Keener, M. M., & Tumlin, K. I. (2023). The Triple-E Model: Advancing Equestrian Research with Perspectives from One Health. Animals, 13(16), 2642.https://doi.org/10.3390/ani13162642

[47] Mathrani, A., Susnjak, T., Ramaswami, G., & Barczak, A. (2021). Perspectives on the challenges of generalizability, transparency and ethics in predictive learning analytics. Computers and Education Open, 2, 100060.https://doi.org/10.1016/j.caeo.2021.100060

[48] Osamika, D., Adelusi, B. S., Kelvin-Agwu, M. T. C., Mustapha, A. Y., Forkuo, A. Y., & Ikhalea, N. (2022). A Critical Review of Health Data Interoperability Standards: FHIR, HL7, and Beyond.https://doi.org/10.26717/bjstr.2018.09.001863

[49] Pham, M. K., Mai, T. T., Crane, M., Brennan, R., Ward, M. E., Geary, U., ... & Bezbradica, M. (2025). Explainable AI for infection prevention and control: modeling CPE acquisition and patient outcomes in an Irish hospital with transformers. BMC Medical Informatics and Decision Making, 25(1), 1-16.https://doi.org/10.1186/s12911-025-03214-1

[50] Raftopoulos, G., Fazakis, N., Davrazos, G., & Kotsiantis, S. (2025). A Comprehensive Review and Benchmarking of Fairness-Aware Variants of Machine Learning Models. Algorithms, 18(7), 435.https://doi.org/10.3390/a18070435

[51] Riley, R. D., Collins, G. S., Kirton, L., Snell, K. I., Ensor, J., Whittle, R., ... & Archer, L. (2025). Uncertainty of risk estimates from clinical prediction models: rationale, challenges, and approaches. bmj, 388.https://doi.org/10.1136/bmj-2024-080749

[52] Sauer, C. M., Chen, L. C., Hyland, S. L., Girbes, A., Elbers, P., & Celi, L. A. (2022). Leveraging electronic health records for data science: common pitfalls and how to avoid them. The Lancet Digital Health, 4(12), e893-e898.

[53] Shahu, S., Ghewade, B., & Kanyal, D. (2025). Pillars of excellence, in healthcare and hospital management: A narrative review on the importance of non-clinical services. Multidisciplinary Reviews, 8(3), 2025093-2025093.

[54] Shen, Y., Yu, J., Zhou, J., & Hu, G. (2025). Twenty-five years of evolution and hurdles in electronic health records and interoperability in medical research: comprehensive review. Journal of Medical Internet Research, 27, e59024.https://doi.org/10.2196/59024

[55] Tabari, P., Costagliola, G., De Rosa, M., & Boeker, M. (2024). State-of-the-art fast healthcare interoperability resources (fhir)–based data model and structure implementations: Systematic scoping review. JMIR Medical Informatics, 12(1), e58445.https://doi.org/10.2196/58445

[56] Tonekaboni, S., Morgenshtern, G., Assadi, A., Pokhrel, A., Huang, X., Jayarajan, A., ... & Goldenberg, A. (2022, April). How to validate machine learning models prior to deployment: silent trial protocol for evaluation of real-time models at ICU. In Conference on Health, Inference, and Learning (pp. 169-182). PMLR.https://doi.org/10.1145/2934664

[57] Tong, R., Zhu, Z., & Ling, J. (2023). Comparison of linear and non-linear machine learning models for time-dependent readmission or mortality prediction among hospitalized heart failure patients. Heliyon, 9(5).https://doi.org/10.13026/8a9e-w734

[58] Ullah, F., He, J., Zhu, N., Wajahat, A., Nazir, A., Qureshi, S., ... & Dev, S. (2024). Blockchain-enabled EHR access auditing: Enhancing healthcare data security. Heliyon, 10(16).

[59] Wilson, A., & Anwar, M. R. (2024). The future of adaptive machine learning algorithms in high-dimensional data processing. International Transactions on Artificial Intelligence, 3(1), 97-107.https://doi.org/10.33050/italic.v3i1.656