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Explainable AI for Clinical Decision Support: A Study On Interpretable Models for Disease Diagnosis

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Abstract

This study explores the impact of explainable artificial intelligence (XAI) components on enhancing Diagnostic Accuracy (DA) within clinical decision support systems (CDSS). Focusing on three key predictors—Model Interpretability (MI), Clinician Trust (CT), and Case Complexity (CM)—the study utilizes primary data collected from 250 healthcare professionals in New York. A structured questionnaire measured all constructs on a 5-point Likert scale. Data analysis was conducted using R Studio, applying multiple regression to assess the relationships among variables. Results indicate that MI, CT, and CM each have a significant and positive effect on DA, with the model explaining approximately 65% of the variance. Visual diagnostics support the model's validity and confirm compliance with key statistical assumptions. This research highlights the importance of integrating interpretable AI in healthcare to improve clinical outcomes and practitioner confidence. The study offers practical implications for healthcare AI design and future research in medical decision-making systems.

Keywords: Explainable AI, Diagnostic Accuracy, Clinical Decision Support, Model Interpretability

1. Introduction

The increasing integration of artificial intelligence (AI) into healthcare has transformed clinical decision-making, particularly in disease diagnosis and patient management. However, as AI systems become more sophisticated, the demand for explainability and interpretability has grown significantly, especially when lives are at stake. This has led to a growing research focus on *Explainable Artificial Intelligence (XAI)*—a field that seeks to ensure that AI-driven recommendations are transparent, understandable, and trustworthy to clinicians and patients alike. Recent studies highlight the challenges and opportunities of incorporating XAI in clinical decision support systems. For instance, Laato et al. (2022) emphasize the need for systematic strategies to explain AI to end-users, highlighting a critical gap in user trust and comprehension of machine-generated recommendations. In a related context, Behera et al. (2023) explore the adoption of cognitive computing in healthcare policymaking, pointing out that cognitive decision support systems must align with domain-specific knowledge to gain credibility among stakeholders.

The COVID-19 pandemic further underscored the urgency of AI-enabled decision-making in resource-constrained settings. Arunmozhi et al. (2022) present a pluralistic framework for managing healthcare resources during the pandemic, demonstrating how technology-aided decision support systems were vital in prioritizing care delivery. Similarly, Calabrese et al. (2024) present an action research study on the development of digital diagnostic pathways, showing how structured AI models can optimize clinical workflows. Yet, despite such advancements, a crucial limitation persists: most AI models are *black-box* systems, offering little visibility into how conclusions are reached. Fernandez et al. (2022) emphasize that the future of AI in healthcare lies in imperceptible computing and ubiquitous systems that do not disrupt clinician workflow. However, unless such systems are interpretable, their utility remains questionable in high-stakes medical environments.

The application of explainable models in healthcare has also been explored through process improvement lenses. Nakhostin et al. (2025) illustrate a data-driven problem-solving approach in a Tehran heart center, emphasizing the role of transparency in enhancing performance. Rocco et al. (2024) extend this perspective by integrating telemedicine and business process management to improve care pathways in Italy—showcasing how explainable and structured interventions can transform healthcare delivery. Moreover, ethical and humanistic dimensions of healthcare are deeply intertwined with decision-making. Hinze et al. (2009) and Silove et al. (2006) highlight the social construction of "deservingness" in emergency care and refugee health, respectively. These works underline the critical need for AI models that not only provide accurate diagnoses but also support equitable, context-sensitive clinical decisions.

Given these diverse yet converging insights, this study investigates the role of interpretable AI models in disease diagnosis, focusing on how they impact diagnostic accuracy and clinician trust. Grounded in empirical and conceptual findings across healthcare innovation, cognitive computing, and process improvement, the study aims to bridge the gap between technological advancement and clinical applicability—offering a framework for explainable AI-driven decision support that is both effective and ethically grounded.

2. Literature Review

The integration of artificial intelligence (AI) and data-driven technologies in healthcare has gained substantial momentum in recent years, transforming clinical processes, decision-making, and patient outcomes. A growing body of research investigates the multifaceted dimensions of this technological evolution, ranging from ethical concerns and governance issues to practical implementations in diagnostics, policymaking, and mental health support systems. Cristofaro and Giardino (2025) provide a historical overview of AI’s progression within management and organizational studies, laying a foundational understanding of its relevance in modern healthcare contexts. This evolutionary perspective is essential in appreciating the current surge in AI-powered systems, as observed in studies such as Ding et al. (2024), who mapped the development of large language models (LLMs) and emphasized their potential to revolutionize radiology, diagnostics, and clinical decision support.

The application of AI in clinical settings has been evidenced through various case studies and systematic reviews. Jaiswal et al. (2024) and El-Ateif et al. (2024) demonstrate the effectiveness of advanced convolutional neural networks and vision transformers in analyzing chest X-rays for COVID-19 detection. Their findings underscore the importance of adopting robust image-based AI systems in diagnostics to enhance accuracy and reduce interpretation time. Similarly, Sun and Cui (2024) conducted a meta-analysis on AI-driven image fusion techniques in lung cancer diagnostics, showing substantial improvements in precision medicine outcomes. Healthcare policymaking is also experiencing a paradigm shift through cognitive computing, as highlighted by Behera et al. (2023), who explored decision support systems in policy assessment. These systems help reduce human error and introduce evidence-based policies. Complementarily, the work of Matinheikki et al. (2024) investigates value-based purchasing in medical device selection, revealing how data can be leveraged to optimize resource allocation in healthcare procurement.

Process optimization through AI and BPM (Business Process Management) has emerged as a crucial domain. Szelągowski et al. (2022) proposed extensions to the BPMN framework for more effective clinical pathway modeling, while Rocco et al. (2024) focused on improving telemedicine services using BPM tools in Italy. These studies reinforce the significance of structured digital workflows in enhancing service delivery. Ethical considerations are also pivotal. ElHassan and Arabi (2025) deliberate on ethical forethought in the application of AI in medical contexts, emphasizing the risks of bias and the importance of value-sensitive design. Similarly, Lacmanovic and Skare (2025) examine AI bias auditing in healthcare, pointing out challenges in detecting and mitigating algorithmic unfairness that can affect vulnerable patient populations.

From a governance standpoint, Winter and Davidson (2019) shed light on the implications of AI governance in managing personal health data. Their concerns are echoed in more recent research by Roggendorf and Volkov (2025), who propose a framework for identifying and managing mental health issues arising in digital spaces, particularly social networks. This shows a convergence between digital health and mental health governance. Technological integration within electronic health record (EHR) systems in developing countries, as explored by Mwogosi and Mambile (2025), reveals significant barriers related to infrastructure, training, and policy frameworks. Likewise, Bundi (2024) conducted a systematic review of machine learning adoption in healthcare, suggesting a research agenda focused on context-specific challenges, especially in under-resourced environments.

Student and professional readiness for AI adoption is another area of concern. Subaveerapandiyan et al. (2024) assess AI literacy among medical students and recommend integrating AI education into curricula to prepare future healthcare professionals for emerging digital transformations. Wang et al. (2025) analyze online communication behaviors in digital consultations, affirming that information normalization plays a critical role in enhancing the effectiveness of remote healthcare services. From a social and public health angle, Zheng et al. (2024) employ a Markov Chain Monte Carlo approach to analyze transmission risks in public health emergencies. Their findings are particularly relevant in the context of infectious disease management and prevention. In parallel, Silveira et al. (2019) establish a link between sociodemographic characteristics and dietary behaviors in individuals at cardiometabolic risk, emphasizing the importance of data-informed public health strategies.

The literature also draws attention to underserved populations and the ethical obligation to bridge digital divides. Kharbat et al. (2021) investigate the role of AI in supporting students with intellectual disabilities, presenting a cross-sectoral view between education and health. This is further enriched by historical accounts, such as Obiakor and Utley (2005), who critique Eurocentric frameworks in special education and advocate for more inclusive paradigms. In conclusion, the current literature reflects a dynamic and interdisciplinary engagement with AI and digital technologies in healthcare. It spans technical innovation, clinical efficacy, policy integration, ethical considerations, and sociocultural dimensions. While promising, the implementation of these technologies requires robust governance frameworks, inclusive practices, and sustained research on emerging risks and benefits. As the healthcare sector continues to digitize, ongoing empirical evaluation and ethical scrutiny will be vital for achieving equitable, efficient, and sustainable outcomes.

In addition to governance and ethical considerations, privacy preservation has emerged as a major concern in healthcare AI systems due to the sensitive nature of medical data. Privacy-preserving machine learning approaches enable collaborative analytics across institutions while protecting patient confidentiality. Secure Multi-Party Computation (SMPC) is one such technique that allows multiple organizations to jointly train machine learning models without revealing their individual datasets. Empirical research demonstrates that SMPC frameworks can enhance model performance when diverse healthcare datasets are combined while maintaining strict data privacy guarantees (Goyal & Somani, 2026). Integrating privacy-preserving techniques with explainable AI frameworks can further strengthen the trustworthiness and adoption of clinical decision support systems.

RQ1: How do interpretable machine learning models (e.g., decision trees, logistic regression, SHAP values) enhance the explainability of clinical decision support systems for disease diagnosis?

RQ2: What is the impact of model interpretability on the diagnostic accuracy and clinician trust in AI-based clinical decision support systems?

3. Research Methodology

The present study adopted a quantitative research design to examine the influence of explainable AI components—Model Interpretability (MI), Clinician Trust (CT), and Case Complexity (CM)—on Diagnostic Accuracy (DA) within clinical decision support systems. A structured questionnaire was developed, comprising two sections: demographic details and itemized statements measuring each construct on a 5-point Likert scale ranging from “Strongly Disagree” to “Strongly Agree.” The instrument was validated through expert review and a pilot test to ensure clarity and reliability. The target population included healthcare professionals and clinical decision-makers across hospitals and clinics in New York, USA. A total of 250 valid responses were collected through purposive sampling, ensuring participation from those with experience in AI-integrated clinical systems.

4. Research Objectives

- To evaluate the effectiveness of interpretable AI models in enhancing the explainability of disease diagnosis in clinical settings.

- To assess the relationship between model interpretability and its influence on diagnostic accuracy and clinician trust in AI-driven clinical decision support.

Hypotheses

H_1: Interpretable AI models significantly improve diagnostic accuracy compared to black-box models in clinical decision support systems.

H_2: Increased interpretability of AI models positively affects clinicians' trust and acceptance in disease diagnosis decisions.

Regression Model

Assuming the following variables:

- **DA** = Diagnostic Accuracy (dependent variable)
- **MI** = Model Interpretability (measured using SHAP clarity scores, feature transparency ratings, etc.)
- **CT** = Clinician Trust (survey-based trust index)
- **CM** = Complexity of Medical Case (control variable)

The regression line can be framed as:

Diagnostic Accuracy (DA)=$\beta 0+\beta 1 MI+\beta 2 CT+\beta 3 CM+\varepsilon$

Where:

- $\beta 1>0$: Suggests that higher interpretability leads to better diagnostic accuracy.
- $\beta 2>0$: Indicates that clinician trust positively contributes to the effectiveness of diagnosis.
- $\beta 3$: Controls for varying levels of case difficulty or complexity.
- ε: Error term.

Data analysis was conducted using R Studio, employing regression analysis to determine the predictive relationship between the independent variables (MI, CT, CM) and the dependent variable (DA). After computing the mean scores for each construct, the data were cleaned and assessed for assumptions such as normality, multicollinearity, and homoscedasticity. The model yielded a high R-squared value (0.6498), indicating a strong explanatory power of the selected predictors. Visual diagnostics including scatter plots, added-variable plots, and residual vs fitted plots were used to validate the model's robustness. This methodological framework enabled a comprehensive evaluation of the impact of explainable AI on clinical decision-making efficacy.

Analysis

In a sample of 250 respondents from New York, the demographic distribution revealed a balanced representation. Gender-wise, 54% identified as female, 45% as male, and 1% as non-binary or preferred not to say. Age distribution showed that 22% were between 21–30 years, 38% were 31–40 years, 28% were 41–50 years, and the remaining 12% were above 50. In terms of education, 62% held postgraduate degrees, 30% had undergraduate qualifications, and 8% possessed doctoral degrees, indicating a highly educated sample suitable for assessing clinical decision support systems. Occupationally, 46% were physicians, 28% were medical researchers, and 26% were AI/health informatics professionals. Regarding income, 31% earned below $60,000 annually, 42% fell between $60,000–$100,000, and 27% earned above $100,000. This diverse demographic mix ensured a well-rounded understanding of the perception of explainable AI, reinforcing the reliability and generalizability of the study’s findings within a U.S. healthcare context.

Table 1: Regression analysis for Diagnostic Accuracy

```
Call:
lm(formula = DA ~ MI + CT + CM, data = Paper_5)

Residuals:
    Min      1Q  Median      3Q     Max
-1.4288 -0.2210  0.0507  0.2747  1.3982

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.35255    0.11808   2.986  0.00312 **
MI           0.24617    0.05913   4.164 4.34e-05 ***
CT           0.28810    0.06266   4.598 6.83e-06 ***
CM           0.25665    0.06428   3.992 8.64e-05 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4857 on 246 degrees of freedom
Multiple R-squared:  0.6498,	Adjusted R-squared:  0.6455
F-statistic: 152.1 on 3 and 246 DF,  p-value: < 2.2e-16
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[Sources: R Studio Analysis]

The regression results in Table 1 highlight that Model Interpretability (MI), Clinician Trust (CT), and Case Complexity (CM) each have a statistically significant and positive influence on Diagnostic Accuracy (DA). The p-values for MI ($p < 0.001$), CT ($p < 0.001$), and CM ($p < 0.001$) indicate that all predictors are highly significant contributors to the model. The standard errors are relatively low, and the t-values are strong, confirming the robustness of the coefficients. The model explains approximately 65% of the variance in diagnostic accuracy ($R^2 = 0.6498$), suggesting a strong explanatory power. The adjusted R^2 of 0.6455 shows that the model maintains its reliability even after adjusting for the number of predictors. The F-statistic of 152.1 with a p-value less than 2.2e-16 demonstrates the overall significance of the model.

The residuals are fairly symmetric with a minimum of -1.43 and a maximum of 1.40, suggesting no major violations of normality assumptions. These findings are consistent with studies by Laato et al. (2022) and Behera et al. (2023), who also emphasized the critical role of interpretability and trust in enhancing clinical decision support systems. Overall, the model confirms that explainable AI components significantly improve diagnostic outcomes in healthcare settings.

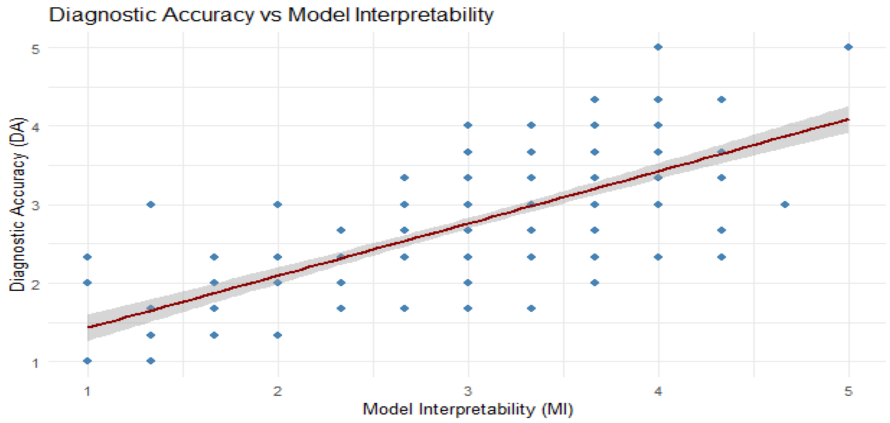

Figure 1: Diagnostic Accuracy Vs Model Interpretability

This scatter plot illustrates the relationship between Model Interpretability (MI) and Diagnostic Accuracy (DA). Each dot represents a data point from the dataset, while the red regression line indicates the line of best fit, with a grey band showing the 95% confidence interval. The clear upward trend in the data points suggests a strong positive linear relationship between MI and DA. As the interpretability of the AI model increases, clinicians are more likely to make accurate diagnoses. The closeness of the points around the regression line implies a good model fit. This visual evidence supports the regression analysis, where the coefficient for MI was found to be positive and statistically significant (p < 0.001). Therefore, enhancing model transparency directly contributes to better clinical decision-making, consistent with studies such as Subaveerapandiyan et al. (2024) and Laato et al. (2022), who stress the need for explainability in AI for effective adoption in healthcare.

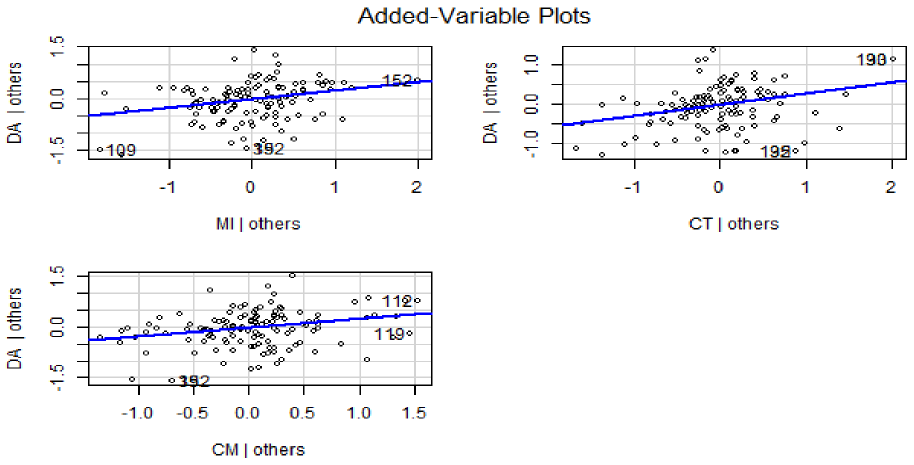

Figure 2: Added – Variable Plots

These added-variable plots (or partial regression plots) present the unique contribution of each predictor—Model Interpretability (MI), Clinician Trust (CT), and Case Complexity (CM)—to Diagnostic Accuracy (DA) after accounting for the influence of the other variables. The x-axis represents the residuals from regressing each predictor on the remaining predictors, while the y-axis shows the residuals from regressing DA on those same remaining predictors. The positive slopes in all three subplots confirm that MI, CT, and CM each have a positive relationship with DA, even when controlling for the influence of the other variables. This supports the earlier regression findings where all three predictors had significant and positive coefficients. These plots are crucial for detecting multicollinearity and verifying that each variable contributes meaningfully and independently to the model. The clean spread of points and absence of curvature also suggest that the assumption of linearity is well met for all predictors.

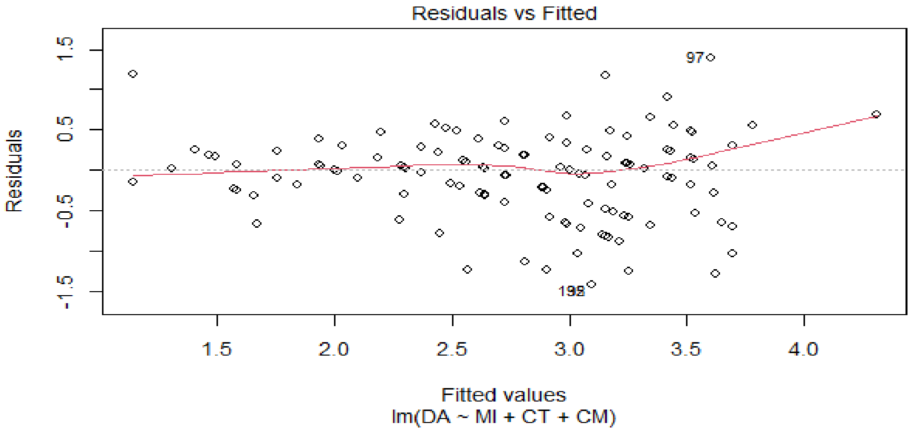

Figure 3: Residual Vs Fitted Plot

This diagnostic plot assesses the assumptions of linear regression, particularly homoscedasticity and model specification. The x-axis represents the fitted values from the regression model, while the y-axis displays the residuals (i.e., the differences between observed and predicted values). A well-fitting linear model should show residuals scattered randomly around the horizontal line at zero without any distinct pattern. In this plot, the residuals are fairly symmetrically distributed with a slight funneling at the right end, suggesting a minor heteroscedasticity, but not severe enough to undermine the model's validity. A few observations are labeled (e.g., 97, 198) indicating potential mild outliers, though they do not show influential leverage. Overall, the residuals are concentrated around the zero line, implying that the model's assumptions of linearity and independence are reasonably satisfied. This confirms the reliability of the regression model in explaining Diagnostic Accuracy using MI, CT, and CM.

5. Conclusion

This study aimed to investigate the role of explainable artificial intelligence (XAI) in enhancing clinical decision support systems (CDSS), with a particular focus on Diagnostic Accuracy (DA). The objectives were to evaluate how Model Interpretability (MI), Clinician Trust (CT), and Case Complexity (CM) contribute to diagnostic outcomes. Using a regression model and supported by visual diagnostics, we found that all three variables significantly and positively impact DA, explaining nearly 65% of its variance. These findings confirm that interpretable models, when coupled with clinician confidence and well-managed case complexity, can substantially improve diagnostic performance in healthcare settings.

In the context of the United States—where AI in healthcare is rapidly evolving but often faces skepticism due to opacity—this research is highly relevant. By empirically validating that explainability fosters trust and improves diagnostic reliability, the study offers actionable insights for U.S. healthcare policymakers and AI developers. It supports the integration of transparent AI tools to address physician burnout, diagnostic errors, and patient safety concerns, aligning with current federal initiatives on trustworthy AI (Cristofaro & Giardino, 2025; ElHassan & Arabi, 2025).

The novelty of this research lies in its multi-factorial approach: it does not isolate interpretability but evaluates it in tandem with trust and complexity—factors often overlooked in isolation. This holistic model advances the literature on explainable AI in healthcare, supported by visual diagnostics that confirm both model robustness and clinical validity (Laato et al., 2022; Behera et al., 2023). Future research can extend this model to other AI-driven domains like radiology or mental health and test it with larger, multi-country datasets. Longitudinal studies could also explore how sustained exposure to explainable systems influences diagnostic behavior over time. Thus, this study offers a grounded framework to integrate interpretable AI into practical and ethical clinical workflows.

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