Hospital Staff Assessment of IT Infrastructure Effectiveness in Facilitating Predictive Analysis in Ghanaian Hospitals

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ABSTRACT
This study assessed the Effectiveness of IT Infrastructure in Facilitating Predictive Analysis in Ghanaian Hospitals. Employing a descriptive survey design, the research targeted three hospitals within the Catholic Diocese of Goaso: St. John of God Hospital, St. Elizabeth Hospital, and St. Edward Hospital. A purposive sampling technique was used to select 90 participants, comprising clinical and administrative staff, including doctors, nurses, IT personnel, and health information officers. Data were collected using a structured web-based questionnaire and analyzed through logistic regression and multicollinearity testing using standard statistical software. Using a descriptive survey and logistic regression analysis, it found that gender significantly influenced adoption, with males more likely to use predictive tools. Other demographics like age, job title, and experience were not significant. While IT infrastructure aided adoption, it was not a sole predictor. The logistic regression model showed strong robustness, and though XGBoost had higher accuracy, it suffered from poor recall and overfitting. Logistic regression was recommended for its balanced performance and interpretability in healthcare, while XGBoost could be optimized for better generalization.
Keywords: Demographic Factors, Predictive Analytics, Healthcare Professionals, Ghana, Technology Adoption, Digital Health, Hospital settings, UTAUT, TAM.
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Introduction

The healthcare system in Ghana is a diverse mix of government, quasi-government, and private providers, each playing a unique role in service delivery (Alhassan et al., 2015). Government hospitals and teaching hospitals are fully state-funded, while quasi-government facilities receive government assistance despite private ownership. Private hospitals, on the other hand, operate independently of state support, often delivering high-quality services at a premium (Alhassan et al., 2015). In an effort to improve accessibility and affordability, the National Health Insurance Scheme (NHIS) was introduced in 2003, shifting from a “cash and carry” system to a broader insurance-based model. Despite its advantages, the NHIS faces persistent challenges including financial constraints, mismanagement, and inadequate coverage of essential health conditions (Alhassan et al., 2015; Derkyi-Kwarteng et al., 2021).

Ghana's healthcare sector continues to grapple with issues such as limited funding, uneven access, and inadequate infrastructure (Oleribe et al., 2019). One of the critical health priorities remains the reduction of maternal and child mortality, which requires not only improved access to care but also enhanced coordination and resource allocation (Kyei-Nimakoh et al., 2016; Conrad & Shortell, 1996). In response to these systemic challenges, emerging technologies particularly healthcare analytics are being explored for their potential to transform healthcare delivery and outcomes.

Studies highlight the growing, albeit gradual, integration of digital technologies in Ghana’s healthcare system. Tools such as electronic health records (EHRs), telemedicine, and mobile health applications have been piloted to bridge service gaps (Acquah-Swanzy, 2015). However, many such initiatives have struggled to move beyond the pilot phase due to poor implementation and sustainability issues (Adjorololo & Ellingson, 2013). Predictive analytics, a subset of healthcare analytics, is slowly gaining attention for its potential to optimize decision-making, enhance resource utilization, and improve patient outcomes (Mensah, 2023; Acheampong, 2012).

Evidence from teaching hospitals such as the Korle Bu and Komfo Anokye Teaching Hospitals demonstrates early adoption of analytics to predict illness trends, manage patient flow, and improve operational efficiency (Govindaraj et al., 1996). Globally, predictive analytics has shown promise in reducing readmission rates, shortening hospital stays, improving staffing during peak times, and enhancing personalized care (Wang et al., 2018; Bao et al., 2017; Singhania & Reddy, 2024). These benefits stem largely from the ability of predictive models to support early interventions and informed clinical decisions (Shams et al., 2015; Baneres et al., 2019).

Yet, the effective use of predictive analytics in healthcare is contingent on several interrelated factors; notably IT infrastructure, data availability, and human factors such as staff readiness and demographic characteristics. While robust IT systems and sound data management are essential enablers, adoption is often influenced by the interplay of individual attributes such as age, gender, job role, and years of experience (Dash et al., 2019; Mant, 2001). Furthermore, the effectiveness of different analytical techniques in predicting adoption is crucial. Traditional statistical models like logistic regression are valued for their simplicity and interpretability, particularly in healthcare settings where transparency of decision-making is essential. In contrast, machine learning approaches such as Extreme Gradient Boosting (XGBoost) offer higher predictive performance in many cases, though they may suffer from overfitting and reduced interpretability (Bao et al., 2017; Singhania & Reddy, 2024).

This study therefore seeks to examine how IT infrastructure supports the adoption of predictive analytics in Ghanaian hospitals, focusing particularly on the role of demographic factors and their interactions with enabling conditions, and comparing the predictive capabilities of logistic regression and XGBoost in modeling readiness to adopt these tools. These objectives would be achieved through the following research questions

1. What is the impact of interactions between demographic factors (e.g., age, years of experience) and predictors such as IT infrastructure on the adoption of predictive analytics?
2. How do logistic regression and extreme gradient boost algorithm compare in terms of predictive accuracy when analyzing the adoption of predictive analytics?

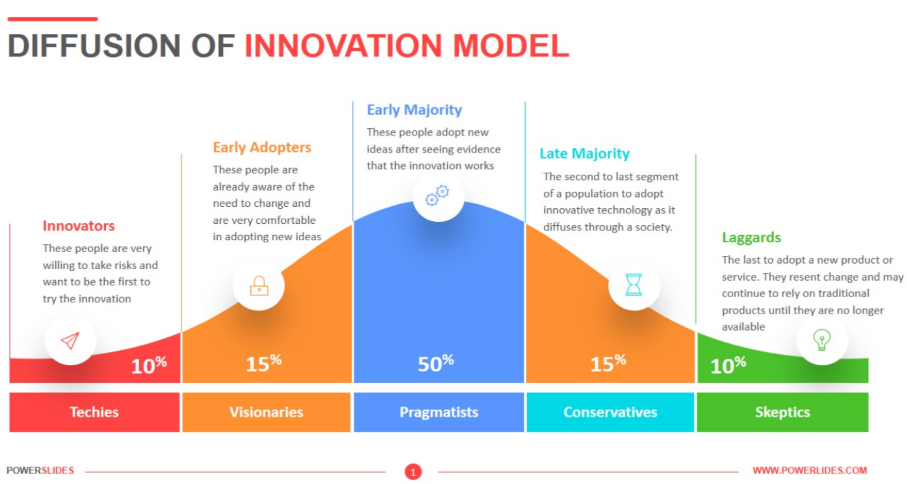
LITERATURE REVIEW

Theoretical Framework of the Study

Diffusion of Innovations (DOI) Theory

The theory was originally developed by Rogers and Havens (1962). According to them, the theory seeks to explain why, how and at what rate new ideas and inventions or technology spread through cultures. They postulate that diffusion is the mechanism by which an innovation is disseminated over time among participants in a social system. They stressed that it is an important framework for understanding how innovations propagate and how adoption can be aided or hampered.

Figure 1: Graphical Representation of the Diffusion of Innovation Theory Model



Rogers and Havens (1962) illustrated the Diffusion of Innovation theory in graphics which is modified in the image in Figure 1. They described how new ideas, products, or technologies spread throughout a society. They categorized the population into five adopter groups depending on their propensity to embrace the innovation. According to them, innovators who make up 2.5% of the population are willing to take risks, they are regarded as technology enthusiasts and are the first to attempt new ideas. Following them are the early adopters who account for 13.5% of the population. These people, according to the proponents, are aware of the need for change and are open to new ideas. Meaning that they are visionaries who help to broaden acceptance of inventions. The next in line are the early majority who make up 34% of the population. They are known for embracing new ideas after seeing evidence that the invention works. This group is normally described as pragmatists who wait for the benefits of innovation to be obvious and proven before jumping onto it. The late majority accounts for 34% of the population. They are more suspicious and only adopt an invention after it has been thoroughly tested and accepted. They tend to be conservative and wary of change. Finally, the last group to embrace an invention are the laggards who account for 16% of the population. They oppose change and prefer to use conventional methods until they are no longer available or practicable. According to Rogers and Havens (1962), the adoption process proceeds sequentially via these categories indicating how social influence and communication routes play a role in the spread of new ideas.

Predictive analytics implementation in Ghanaian hospitals, as suggested by Adjorlolo and Ellingsen (2013), requires the use of novel healthcare technologies. The theory's principles of innovation adoption is in a position to help hospitals plan the implementation of predictive analytics while keeping stakeholders involved (Putteeraj et al., 2022). Macias et al. (2023) asserts that effectively integrating predictive analytics can improve patient outcomes by tackling adoption barriers and utilizing influencers within the healthcare system.

The Technology Acceptance Model (TAM)

According to Davies (1989), Technology Acceptance Model is a theoretical framework that describes how users accept and use technology. He explains that TAM is an extension of the Theory of Reasoned Action (TRA) that was designed primarily to study user acceptance of information systems and technology. Machdar (2016) also explained that with this concept, perceived ease of use and perceived usefulness have a major impact on user decisions.

Understanding how healthcare personnel view predictive analytics tools in Ghanaian hospitals might assist develop and execute these technologies in ways that increase their adoption and usage (Antwi et al., 2014). Hospitals can enhance patient outcomes by making predictive analytics more accessible and effective (Suresh, 2016). As a result, Habimana (2020) suggested that implementing these theories in the adoption and application of predictive analytics will greatly improve patient outcomes in Ghanaian hospitals by ensuring that the technology is effectively integrated, accepted and used by health professionals.

Global Perspectives on Predictive Analytics in Healthcare

According to a study by Amarasingham et al (2014), the use of analytics in the healthcare sector is becoming increasingly popular globally because of its ability to enhance outcomes, operational efficiency and overall quality of healthcare services. The study also noted that predictive analytics allows healthcare professionals to anticipate health events, resources and enhance clinical decision making. Hamza (2023) suggested that predictive analytics plays a role in transforming healthcare systems by promoting data driven decision making globally. This leads to improved outcomes and effective healthcare services in the long run. According to Kuvvetli et al. (2021), predictive analytics played a role in North America due to its healthcare system and substantial investments in health information technology infrastructure. They highlighted the importance of models during the COVID-19 crisis for guiding resource distribution and predicting outcomes and playing a vital role in responding effectively to the pandemic.

In Europe, the growth of predictive analytics integration is on the rise. There is a focus on enhancing care and reducing healthcare expenses (Carter et al., 2022). Partnerships between tech firms and healthcare providers are helping the market by creating approaches for managing population health and clinical uses (Horgan et al., 2019).

The use of analytics is rapidly increasing in the Asia Pacific region due to the growing healthcare needs and advancements in healthcare infrastructure (Raghavan et al., 2021). In China specifically, predictive analytics is being employed to address the rising cases of diseases and enhance healthcare services in both urban settings (Ding et al., 2021).

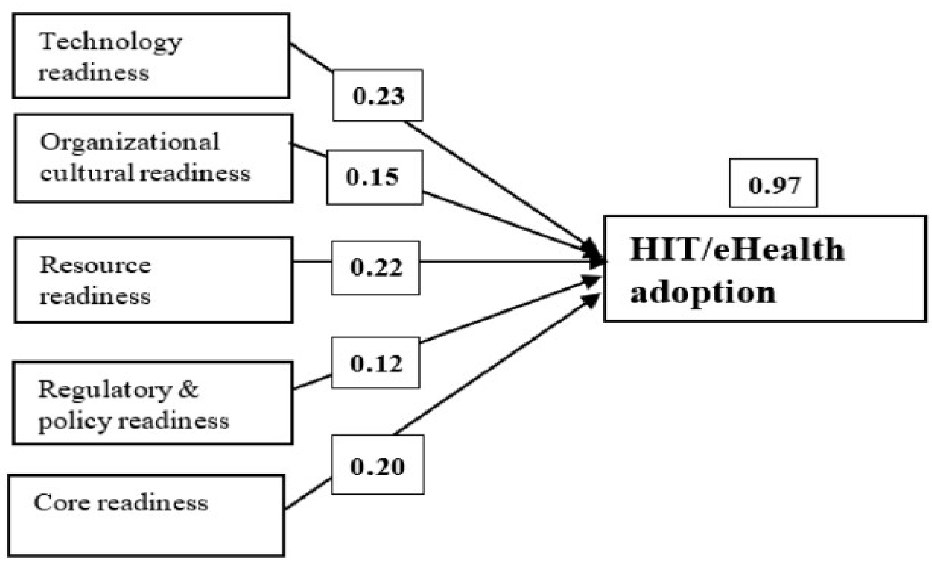
According to Ibeneme et al. (2021), predictive analytics is making an impact in healthcare across regions in Africa by leveraging data to improve patient results and efficiency while optimizing resources usage. African nations are progressively embracing health tools like electronic health records systems (EHRs) and telemedicine to enhance healthcare services delivery in remote and underserved areas, as highlighted by Bukachi and Pakenham-Walsh (2007). African authorities are gradually introducing eHealth and mHealth programs to meet healthcare demands by facilitating diagnosis based on information and delivering treatment and prevention measures (Batani and Maharaj, 2022). According to the insights shared by Batani and Maharaj (2022), this strategy is essential for overseeing healthcare resources and guaranteeing fair access to top notch care throughout the region.

In a study by Yusif et al. (2020), they conducted research to evaluate how Ghana's health system is prepared for health information technology (HIT) and eHealth systems through methods. The researchers distributed questionnaires to healthcare professionals working across public health institutions to gather insights on technological readiness (TR), organizational capacity readiness (OCR), resource readiness (RR), policy readiness (PR) and commitment readiness (CR).

They utilized a method called regression analysis to determine how well these factors could predict readiness for handling health information technology. They assessed the models effectiveness by conducting an F-test to measure its significance and using R^2 to gauge the amount of variance explained by the model.

The researchers found that all the five factors (TR, OCR, RR, PR and CR) had an influence on the level of preparedness for Health Information Technology at public healthcare facilities in Ghana. The multiple correlation coefficients indicated a relationship among these factors and HIT readiness assessment effectiveness. With an R^2 vale of 0.97 in place of 1.00 indicates that these factors account for 97 percent of the variability observed in HIT preparedness.

Figure 2: Graphical Representation of the Findings of Yusif et al. (2020).



Yusif et al. (2020) illustrated a graph showing the findings of the study on how Ghanaian public healthcare centers are equipped to adopt HIT or eHealth practices. Their model displays factors affecting HIT/eHealth implementation based on their path coefficients. Technology readiness emerges as the predictor of HIT/eHealth adoption with a path coefficient of 0.23. Resource availability is closely connected with a coefficient of 0.22 underscoring the importance of having resources for implementation. Core readiness with a coefficient of 0.20 denotes fundamental elements like infrastructure and crucial health services that aid in HIT/eHealth implementation. Organizational cultural readiness indicated by a coefficient of 0.15 highlights the role of organizational culture in either fostering or hindering adoption. Lastly, regulatory and policy readiness with a correlation of 0.12 demonstrates how regulatory structures and policies impact adoption. The study findings show that these factors play a role in the adoption of HIT/eHealth services in regions like Ghana and highlight key areas that need attention for successful implementation with an impressive model fit score of 0.97.

The level of preparedness in technology, capacity and resource availability was crucial in determining the readiness of hospitals to deploy Health Information Technology. Similarly, the readiness in terms of policies and commitment of leadership played a role in ensuring the implementation of HIT systems.

The results show that healthcare institutions in Ghana are well informed and equipped to adopt health information technology systems with Teaching Hospitals demonstrating this awareness prominently. The research proposes that successful implementation of HIT requires advancement not only in technology but also organizational support and policy endorsement. The study recommended that to enhance eHealth readiness, support from government and healthcare leaders should focus on enhancing proficiency and establishing a policy framework.

The results of this research go against the perspective put forth by Batani and Maharaj (2022) who argue that solely having technologies is insufficient for enhancing healthcare quality and efficiency. Batani and Maharaj (2022) on the other hand propose a shift from digital health to data driven healthcare by employing predictive analytics like machine learning and big data to enhance health outcomes. Furthermore, some experts highlight the downsides of relying much on technological readiness without addressing the socioeconomic and cultural factors that significantly influence the adoption and effectiveness of HIT in developing countries.

In terms of research directions put forth by the authors, they proposed that upcoming studies should concentrate efforts towards creating and confirming instruments for this purpose due to the lack of established benchmarks for evaluating eHealth readiness. Additionally, they suggested the need for assessment into the adoption readiness factors to environment and other scenarios beyond Ghana borders to ensure that the results hold relevance across a wide range of developing nations.

In order to delve deeper into the preparedness of healthcare facilities in Ghana for incorporating technology advancements, Adjorlolo and Ellingsen (2013) conducted an interpretive case study to assess the University of Ghana Hospital's capacity for implementing an Electronic Patient Record (EPR) system. This method of research enabled an exploration of the organizational and psychological factors that impact the adoption of EPR. The study involved gathering information from 30 participants comprising healthcare professionals and administrators through methods such as structured interviews, observations, document analysis and questionnaires. The main steps in the study methodology involved selecting participants who played a role in managing records and administration processes. They used data collection tools such as formal interviews lasting approximately an hour each, observations, field notes and closed ended questionnaires. For analyzing the data gathered, they employed techniques based on Miles and Huberman (1994) approach for a good quantitative analysis using SPSS.

The research shared details regarding the University of Ghana Hospital preparedness for implementing EPR systems in terms of organization, finance, management and skills. Their financial management were commendable as the hospital managed to secure funds from the University of Ghana. Their ICT setup, including 40 desktop computers and 5 printers, across departments were having internet access. Nonetheless, the ICT department was noted to be lacking resources which highlighted an area in need of improvement. The hospital provided its employees with computer training and provided additional on-the-job training for the EPR system to ensure that the staff were well prepared for the transition ahead. From observation by the authors, there was a generator in place at the hospital to ensure a power supply and minimize any potential power interruptions. Regarding the readiness of healthcare professionals, a survey indicated that the staff were eager and optimistic about integrating the EPR system into their workflow. The survey revealed that; the staff anticipated that it would significantly enhance data management process and elevate healthcare service delivery, the existing paper based method of keeping records faced challenges like writing and losing records that health workers believed the EPR system would solve, the EPR system was anticipated to offer improved storage space for data and better options for accessing and sharing information to ensure thorough records, these improvements aimed to simplify processes and enhance the quality of care provided by the hospital.

The research paper highlighted five areas that required investigation to enhance the understanding of EPR implementation readiness and effectiveness. To begin with, it suggests conducting studies to monitor the implementation progress over a period and evaluate the long-term sustainability and influence of the EPR system on healthcare practices within hospitals. Additionally, exploring studies among hospitals or regions was proposed as another avenue for future research. Investigating these studies, according to the report, could help identify methods by evaluating the readiness and success of implementing EPR systems in other situations as this method of comparison may pinpoint factors that foster successful EPR integration and create strategies that can be replicated in other environments. Furthermore, the research underscored the importance of considering end user involvement in the design and tailoring of EPR systems. On the issue of user design, the study highlighted the potential for enhancing the usability and acceptance of the system by aligning it with the needs and preferences of its users such that implementing such an approach could lead to a productive utilization of the EPR system that would eventually enhance health outcomes.

The study by Adjorlolo and Ellingsen (2013) provides insights into the preparedness for implementing EPR systems, however, other researchers have offered different viewpoints. Sood et al. (2008) underscores that developing countries often face resource limitations that could impede the execution of large-scale ICT initiatives like EPR systems. In their assessment of the University of Ghana Hospital's preparedness for EPR systems, Adjorlolo and Ellingsen (2013) identified areas for improvement as well as areas of strength in their research findings and implications that can offer valuable guidance for similar initiatives in other hospitals across Ghana. Nevertheless, the concerns raised by researchers underscore the challenges in such endeavors and emphasize the ongoing need for research and adjustments to align with local contexts.

METHODS

Research Design

This study employed a descriptive survey design as its primary methodological framework. This design was selected due to its effectiveness in capturing and describing the perceptions and readiness levels of hospital personnel regarding the adoption of predictive analytics. As Wang and Hajli (2017) note, descriptive surveys are instrumental in systematically obtaining information relevant to understanding institutional preparedness for technological innovations. The use of surveys facilitated the collection of quantifiable data that can be analyzed to identify patterns, trends, and correlations, thereby enabling generalizations with statistical significance (Martin & Bridgmon, 2012). A purposive (non-probabilistic) sampling method was adopted to ensure the selection of participants with specific knowledge and expertise in hospital management and healthcare technology. This sampling approach was appropriate for targeting individuals directly involved in decisions related to health information systems and patient care (Burns et al., 2008).

Participants

The study focused on three hospitals within the Catholic Diocese of Goaso, namely: St. John of God Hospital, St. Elizabeth Hospital, St. Edward Hospital. A total of 90 participants were involved, with 30 individuals selected from each hospital. The participants comprised a mix of hospital administrators, IT personnel, health information officers, and clinical experts such as Doctors, Nurses, Midwives, Laboratory Technicians, Pharmacists. The sample was 52% male and 48% female. 46.67% of the participants were below 34 years of age.

Instruments

Data were collected using a structured, web-based questionnaire designed to assess the impacts of demographic factors on the adoption of predictive analytics. The questionnaire was disseminated electronically via email and WhatsApp communication channels to enhance accessibility and participation. Participants received a clear explanation of the study's objectives and a consent form outlining the nature of their involvement, the confidentiality of their responses, and their right to withdraw at any stage.

Ethical approval for the study was obtained from the Diocese Health Service Directorate, which oversees the administration of the participating hospitals. Informed consent was obtained from all participants prior to data collection. Consent forms explicitly stated the purpose of the study, the data collection process, the voluntary nature of participation, and measures to ensure anonymity and confidentiality. To ensure credibility and dependability, several validation strategies were implemented. Firstly, triangulation was employed through the integration of multiple data sources to enhance the robustness of the findings (Lemon & Hayes, 2020). An initial pilot survey was conducted to refine the questionnaire items, enhance clarity, and improve response accuracy. Additionally, member validation was carried out by presenting preliminary findings to a subset of participants to verify the accuracy of the interpretations and conclusions drawn from the data (Birt et al., 2016). These measures contributed to the overall trustworthiness and rigor of the research process.

RESULTS AND FINDINGS

Research Question 1

What is the impact of interactions between demographic factors (e.g., age, years of experience) and predictors such as IT infrastructure on the adoption of predictive analytics?

Table 1: A logistic regression with two different models one with control variables and interactive variable.

	Model 1	Model 2
	AOR (Std Error)	AOR (Std Error)
Gender		
Female	Reference	Reference
Male	5.158 (3.155)	5.072* (2.920)
Job Title		
Administrative Staff 1	ref	Ref
Doctor/Nurse/Midwife	3.218 (2.985)	3.416 (2.527)
Other Clinical Staff	6.860 (5.818)	6.779* (3.823)
Interaction Term		
Female#Administrative Staff 1	Reference	Reference
Female#Doctor/Nurse/Midwife	Reference	Reference
Female#Other Clinical Staff	Reference	Reference
Male#Administrative Staff 1	Reference	Reference
Male# Doctor/Nurse/Midwife	-0.391 (2.763)	-0.494 (2.515)
Male#Other Clinical Staff	-8.483 (6.570)	-8.368* (5.020)
Age		
Below 34 years	Reference	
35-54 years	-0.516 (1.540)	
55 years and above	-0.435 (1.573)	
How effective are the data management processes in your hospital		
Ineffective	Reference	Reference
Neutral	-1.625 (3.101)	-1.637 (2.548)
Effective	-4.529 (4.051)	-4.432 (3.079)
Years of Experience in Healthcare		
Below 5 years	Reference	Reference
6-10 years	2.358** (1.181)	2.245* (1.232)
11 years and Above	1.239 (1.769)	1.015 (1.523)
Where do you work		
St. Edward Hospital	Reference	Reference
St. Elizabeth Hospital	-1.964* (1.177)	-1.968* (1.069)
St. John of God Hospital	-2.408 (1.928)	-2.394 (1.782)
How would you rate the current IT infrastructure in your hospital		
Poor	Reference	Reference
Average	0.536 (2.315)	0.568 (2.779)
Good	0.0615 (1.783)	0.0243 (2.101)
If yes, how would you rate the effectiveness of the electronic health records system		
Ineffective	Reference	Reference
Neutral	-3.885 (3.806)	-3.831 (3.173)
Effective	-1.052 (1.793)	-1.008 (1.492)
How do you assess your familiarity with predictive analytics		
Not familiar at all	Reference	Reference
Moderately familiar	-2.563** (1.082)	-2.377 (1.468)
Very familiar	-1.271 (1.903)	-1.169 (2.046)
Have you received any training in predictive analytics related to healthcare		
No	Reference	Reference
Yes	-1.931 (2.039)	-1.851 (1.487)

How willing are you to implement predictive analytics in your daily work		
Not willing	Reference	Reference
Very willing	0.368 (1.740)	0.199 (1.640)
What type of training do you think is necessary for effective use of predictive analytics		
On-the-job training, Certification programs	Reference	Reference
Online courses, On-the-job training, Certification programs	-0.892 (1.351)	-0.961 (1.650)
Workshops, On-the-job training, Certification programs	0.257 (2.434)	0.255 (2.827)
Workshops, Online courses, On-the-job training, Certification programs	-0.840 (1.964)	-0.946 (1.852)
"There is cultural resistance to adopting new technologies in my hospital"		
Disagree	Reference	Reference
Neutral	-0.595 (3.718)	-0.667 (2.967)
Agree	4.350^{**} (1.915)	4.022^{*} (2.279)
"There are organizational barriers that hinder the implementation of predictive analytics in my hospital"		
Disagree	Reference	Reference
Neutral	-6.972^{**} (2.970)	-6.686^{**} (2.729)
Agree	-1.500 (1.671)	-1.439 (1.708)
_cons	6.360 (4.490)	6.062 (4.573)
N	90	90
r2		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Logistic regression results in Table 1 further investigate the predictors of the propensity of healthcare professionals to deploy predictive analytics in Ghanaian hospitals, focusing on interaction effects. Analysis by variables of gender, job role, and experience reveals some striking patterns, coupled with the interaction terms. Gender also tends to play a major role, while males are significantly more likely than females to adopt predictive analytics. AOR = 5.072 and $p < 0.1$.

With regards to the interaction of gender with job title, whereas the category "Other Clinical Staff" is much more likely to adopt predictive analytics, AOR = 6.779, $p < 0.1$, this effect is considerably dampened by males coming from this job category, AOR = -8.368, $p < 0.1$.

The results also show that with an AOR of -1.968 and $p < 0.1$, St. Elizabeth Hospital is less likely to adopt predictive analytics than St. Edward Hospital.

The result from Table 1 is expected from the Gender Role Theory by Eagly (1987), which suggests that cultural expectations about gender roles could affect professional choices and explain why males are more willing to adopt new technologies.

More importantly, interaction of gender with job title presents some interesting insights. Whereas the category "Other Clinical Staff" is much more likely to adopt predictive analytics, AOR = 6.779, $p < 0.1$, this effect is considerably dampened by males coming from this job category, AOR = -8.368, $p < 0.1$. This could indicate that clinical staff in general may be open to using predictive analytics, but gendered dynamics in the group inhibit the adoption, a finding which aligns with Social Role Theory, stating that social expectations strongly influence professional behavior.

Besides, the experience in the health sector emerges as a significant determinant of adoption because professionals with 6-10 years of experience are more likely to adopt predictive analytics use AOR = 2.245, $p < 0.1$. It thus supports Human Capital Theory, as stated by Becker (1964), which reasoned that workers with a moderate level of experience may have acquired adequate expertise to feel confident in adopting new technologies such as predictive analytics but are still flexible toward change.

It further explains that the organizational context also played a role in the survey, such that the likelihood of St. Elizabeth Hospital adopting predictive analytics was lesser compared to St. Edward Hospital, with an AOR of -

1.968 and $p < 0.1$. This is in line with the Diffusion of Innovation Theory propounded by Rogers, 2003, which postulates that institution culture and infrastructure might influence the rate at which technology is adopted. Agreeing to the statement of benefits from predictive analytics greatly increases the chances of adoption (AOR = 4.022, $p < 0.05$), supporting TAM-which maintains perceived usefulness as one of the main drivers for the acceptance of technologies (Davis, 1989).

Table 2: Diagnostic and Robustness Check

<table>
<tr><th>Metrics</th><th colspan="2">Model 1</th><th colspan="2">Model 2</th></tr>
<tr><td rowspan="2">Confusion Matrix</td><td>68</td><td>6</td><td>68</td><td>7</td></tr>
<tr><td>2</td><td>14</td><td>2</td><td>13</td></tr>
<tr><td>Sensitivity</td><td colspan="2">97.14%</td><td colspan="2">97.14%</td></tr>
<tr><td>Specificity</td><td colspan="2">70.00%</td><td colspan="2">65.00%</td></tr>
<tr><td>Positive predictive value</td><td colspan="2">91.89%</td><td colspan="2">90.67%</td></tr>
<tr><td>Negative predictive value</td><td colspan="2">87.50%</td><td colspan="2">86.67%</td></tr>
<tr><td>Correctly classified</td><td colspan="2">91.11%</td><td colspan="2">90.00%</td></tr>
</table>

The key diagnostics and robustness checks in Table 7 demonstrate very important insights into the performance of the two logistic regression models analyzing the factors influencing the adoption of predictive analytics in Ghanaian hospitals. Both models have a high predictive power, with marginal differences in performance, thus suggesting that the models are robust in their identification of adopters of predictive analytics.

Regarding sensitivity, which is the share of a model that correctly identifies healthcare professionals willing to adopt predictive analytics, sensitivity stands very high at 97.14%. This means that the models capture the majority of those people who are inclined toward implementing predictive analytics. High sensitivity in this regard is quite crucial, as this helps in identifying possible early adopters of innovative health technologies, which again is supported by Diffusion of Innovation Theory, where Rogers claims that identification of innovators and early adopters is crucial for any technology to diffuse internally within an organization.

Specificity, on the other hand, has to deal with the models correctly identifying the cases that are unwilling to adopt predictive analytics. It is much lower at 70.00% for Model 1 and 65.00% for Model 2. This lower specificity means that both these models will tend to have a high level of false positives-those misclassified as adopters but really not. This difference can therefore indicate the underlying organizational hurdles in the way of the adoption of technology, such as resistance to change or lack of training, which finds its basis in support from the Technology Acceptance Model. According to TAM, perceived usefulness and ease of use are two important factors that influence the acceptance of any new technology; thus, this may not be captured by both the models. The PPV of both models is equally high: 91.89% for Model 1 and 90.67% for Model 2, indicating a majority in both models actually adopt predictive analytics. The NPV is equally impressive at 87.50% for Model 1 and 86.67% for Model 2, suggesting both models do an effective job of distinguishing non-adopters. Both models showed very high overall classification accuracy: 91.11% and 90.00% of cases correctly classified for Models 1 and 2, correspondingly. This robustness underlines the usefulness of the model in predicting the adoption of predictive analytics in healthcare by developing specific interventions, such as training and improvement of infrastructure, in order to further increase adoption rates.

Research Question 2

How do logistic regression and extreme gradient boost algorithm compare in terms of predictive accuracy when analyzing the adoption of predictive analytics?

Table 3: Diagnostic and Robustness Check of the Extreme Gradient Boost Algorithm

Metrics	precision	recall	f1-score	support
Not Effective = 0	1.00	0.25	0.40	4
Effective = 1	0.82	1.0	0.90	14
accuracy			0.83	18
macro avg	0.91	0.62	0.65	18
weighted avg	0.86	0.83	0.79	18
Robustness Checks (Cross Validation Checks)				
5-fold Cross Validation		72.22%		
Average Stratified K-Fold		71.11%		

The results in Table 3 present the diagnostic and robustness checks for the XGBoost Algorithm, testing the model performance classification of outcome classes as either "Not Effective" or "Effective" basing on the adoption of predictive analytics in Ghanaian hospitals. These results are discussed below in light of precision, recall, f1-score, accuracy, and robustness to evaluate the model's effectiveness.

Precision of the "Not Effective" class is 1.00; all its predicted instances are actual "Not Effective". However, its recall is low, amounting to 0.25, meaning that the model identified only 25% of the actual "Not Effective" cases. That means it tends to have more false negatives, where cases are actually "Not Effective" but not captured by the model. Whereas its recall is 1.0 for the class "Effective", meaning the model correctly captures all the actually true "Effective" cases, with a precision of 0.82, that suggests a few false positives. These findings are in concert with TAM, in that perceived usefulness and perceived ease of use drive the adoption. The model identifies the adopters who could show the perceived benefits of predictive analytics in improving healthcare outcomes.

This means that the overall accuracy of the model is high at 83%, but the class imbalance is a problem, as shown by the macro average f1-score, which is rather low at 0.65; the model performance heavily leans toward the class "Effective." This agrees with the Diffusion of Innovation Theory by Rogers 2003, which postulates that early adopters of any innovation, like predictive analytics, tend to be more identifiable than non-adopters because they are more open to change.

About robustness, the model performs consistently well with a cross-validation accuracy of 72.22% and an average stratified k-fold validation of 71.11%, thus showing generalisability. These checks for robustness ensure that the performance is not overfitted on the training data, but it brings out the fact that further improvements the model could undergo are reducing the rate of false negatives for non-adopters.

Figure 3: A graphical representation of the xgboost algorithm tree

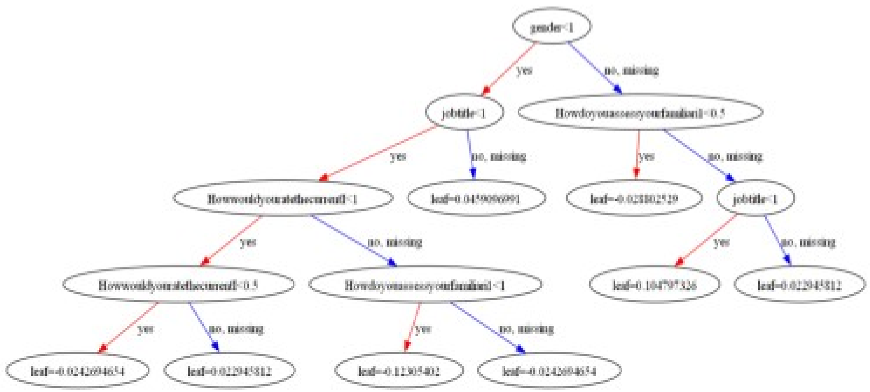
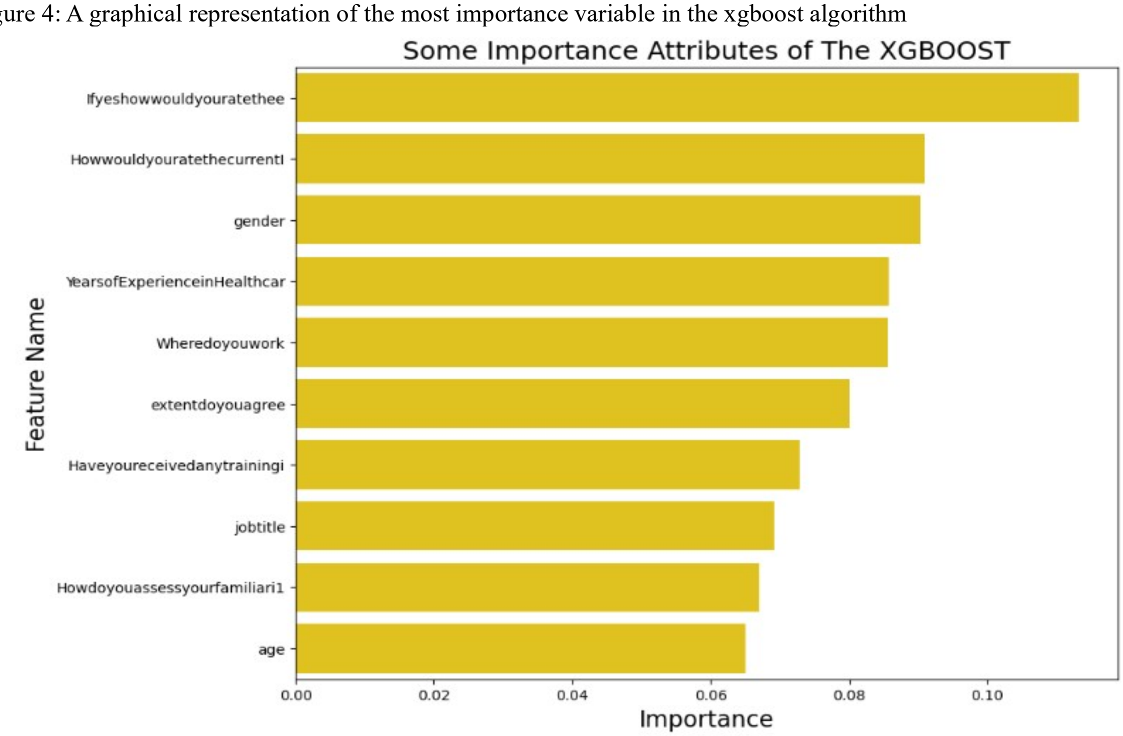


Figure 4: A graphical representation of the most importance variable in the xgboost algorithm



In the plot above (Figures 3 and 4), "If yes how would you rate how would you rate the effectiveness of EHRs" has the highest gain feature, followed by "How would you rate the current IT infrastructure", and "gender". Other important features are "Years of Experience in Healthcare", "Where do you work", and "extent you agree there is cultural resistance to adopting new technologies in my hospital ", which also have considerable importance but slightly lesser.

Figure 5: A graphical representation of the confusion matrix for the xgboost algorithm

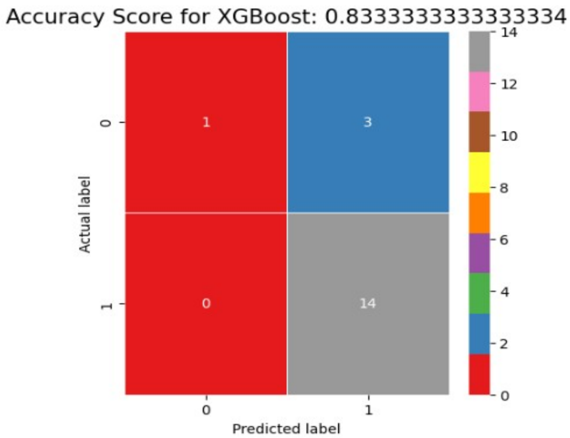
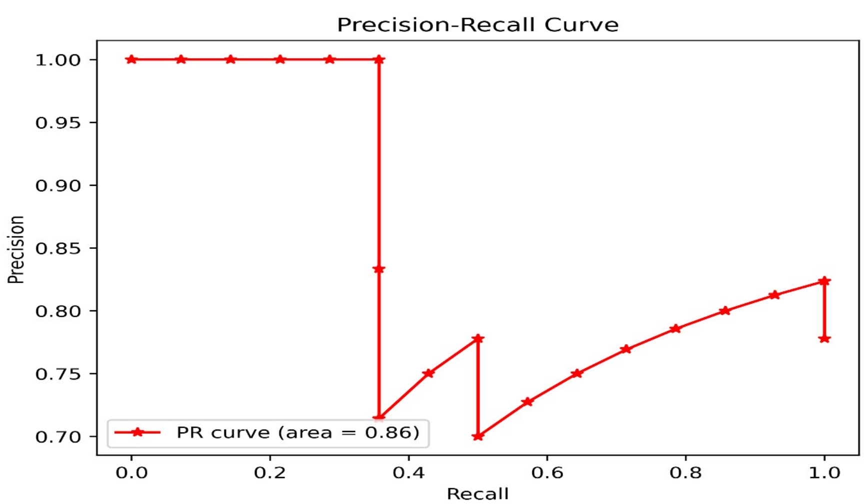


Figure 5 represents the confusion matrix with respect to the performance of the XGBoost model. This gives an overall outlook into the predictions of the model against the actual labels, at an accuracy score of 83.33%. The top-left quadrant contains the true negatives (TN), where the model correctly predicted the negative class of 0. There is 1 correct prediction in this regard. The top-right quadrant corresponds to false positives-FP-and points out that the model has incorrectly predicted class 1 positive when, in fact, it was negative. It contains 3 FPs, which means that the model was overly optimistic for those instances.

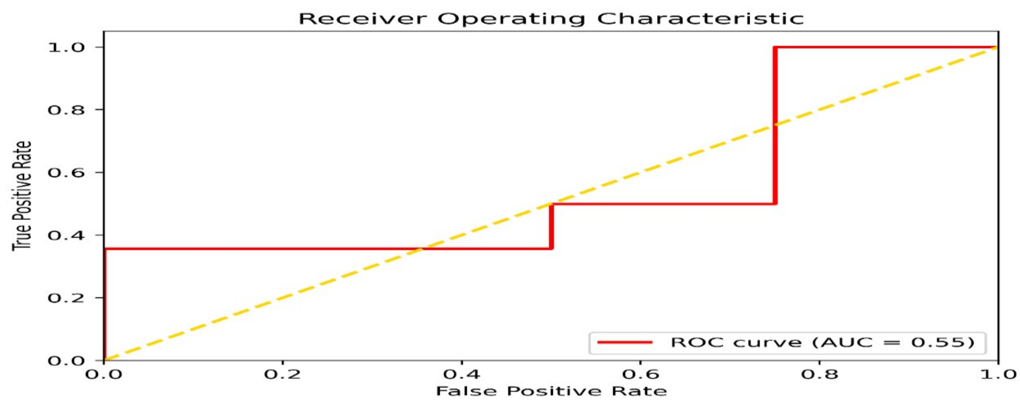
The bottom-left quadrant shows the false negatives, FN: these are the cases that the model predicted as negative, 0, when actually it was positive, 1. Quite interestingly, there are 0 false negatives, which means the model is doing pretty good at catching the positive class. The bottom-right quadrant is the true positive, where the correct prediction of the model falls into the positive class-say, 1. It has a total of 14 and shows the strong point of the model for correctly identifying the positives. The overall accuracy is 83.33%, depicting that the model has rightly classified most data points. However, 3 false positives indicate further improvement in reducing over-prediction of the positive class.

Figure 6: A graphical representation of the Precision-Recall Curve of the gradient extreme boost algorithm



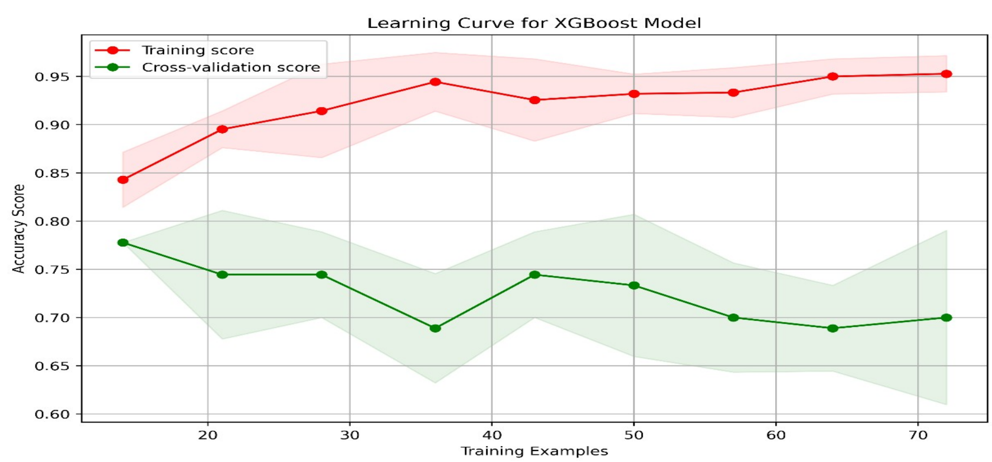
On this graph (figure 6), the PR curve has a value of 1.00 for precision with low values of recall. As the recall increases, the precision drops greatly to very minimal values. The AUC-PR is 0.86, representing a very good result, since this further reflects the good performance of the model in terms of class discrimination.

Figure 7: A graphical representation of the Receiver Operating Characteristic (ROC) of the gradient extreme boost algorithm.

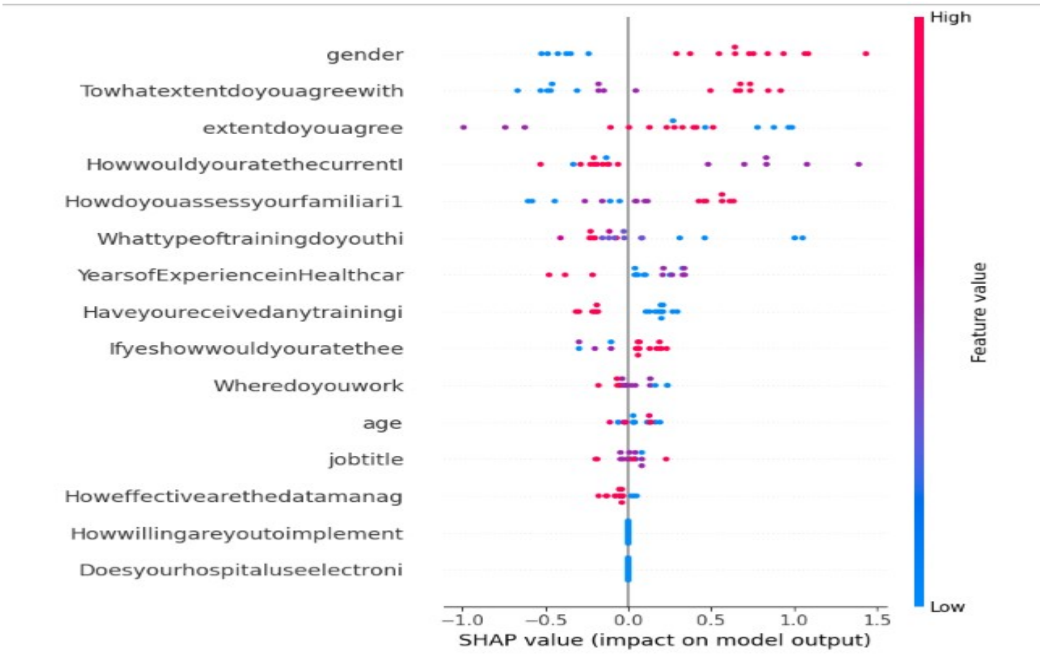


From figure 7, the AUC for this model is 0.55, which is slightly better than a random classification.

Figure 28: A graphical representation of the Learning of the curve of the gradient extreme boost algorithm



From figure 8, the training score is rather high, about 85%. This goes on increasing further before finally stabilizing around 95% as the number of training examples increases. With the cross-validation score it starts at about 75% and seesaws down with an increasing number of training examples to a final value of around 70%.
Figure 9: A graphical representation of the SHAP vale of the gradient extreme boost algorithm



One can see figure 9 that “gender” and “There is cultural resistance to adopting new technologies in my hospital” have the highest impact on model predictions, with higher SHAP values for gender, possibly males, tending to push the prediction towards "Effective."

Extreme Gradient Boosting Algorithm

The Extreme Random Boosting Algorithm was developed based on an advanced implementation of gradient boosting, XGBoost Classifier, which is very efficient and ensures high performance. Gradient boosting is commonly regarded as one of the most well-known methods for model improvement through the iterative learning and aggregation of weak learners. In this respect, GridSearchCV from sklearn.model_selection was used for hyperparameter tuning in the model and to choose the best performance. GridSearchCV is an exhaustive search technique that finds the best parameter values through cross-validation on a variety of configurations.

First, a parameter grid was defined that included various configurations to be tested for the most important hyperparameters. For the current model, these included the number of trees in the model-n_estimators; the maximum depth of each tree, hence affecting model complexity-max_depth; the step size during optimization-learning_rate; and the regularization parameter penalizing overly complex models-gamma. The following ranges of hyperparameter tunning were verified: n_estimators: 100, 200; max_depth: None, 5, 10; learning_rate: 0.1, 0.01, 0.001; gamma: 0, 0.1, 0.2. The grid search went through the performance of all possible combinations using 5-fold cross-validation and chose the optimal hyperparameters: gamma = 0.2, learning_rate = 0.1, max_depth = None, n_estimators = 100.

Now that the optimal hyperparameters have been identified, an XGBoost classifier is created and retrained with these identified values. This final configuration includes a learning rate of 0.1, gamma of 0.2 that regulates model complexity and overfitting, and 100 estimators for boosting, with a very strong balance between model flexibility and regularization. This set provides robust performance on predictive tasks since the model learns with the data's complexity while preventing overfitting of the model.

Figure 19 is the chart showing feature importance of the attributes used in the XGBoost model. Feature importance describes the contribution of each feature to the predictive power of the model, and therefore helps to identify which variable most influences the decisions made by the model. In the plot above, "If yes how would you rate the effectiveness of EHRs" has the highest gain feature, followed by "How would you rate the current IT infrastructure", and "gender". These features most greatly contribute to the predictions of this XGBoost model and might have had the most influence on the target outcome.

Other important features are "Years of Experience in Healthcare", "Where do you work", and "There is cultural resistance to adopting new technologies in my hospital", which also have considerable importance but slightly lesser. Features like "age" and "How do you assess your familiarity with predictive analytics" are lower in terms of their importance, hence less contributing to the model's prediction. The feature importance plot above tells about what variables drive a model's predictions, giving insight into areas one might want to focus on in improving the model, or what factors drive the outcome.

Figure 22 shows a Precision-Recall Curve, which is always a useful graph to understand model performance in general but certainly more specifically when dealing with imbalanced datasets. It charts the trade-off between precision, or the ratio of true positives out of all positive predictions, and recall, or the ratio of true positives out of all actual positives at various threshold settings. The results indicates how highly precise the model is but does badly on true positives since only a small portion is captured. As the recall increases, the precision drops greatly to very minimal values. The fact that with increased captured true positives the model tends to lose its grip on precision is why the model gets bad with captured true positives. This happens to many models whereby at increased sensitivity, lots of false positives are accepted, hence lowering the precision.

The AUC-PR of 0.86 represents a very good result since this further reflects the good performance of the model in terms of class discrimination. In fact, its high AUC-PR value brings evidence about the excellent balance between precision and recall for the proposed approach when the data are imbalanced and one class "Effective" is dominating. This PR curve is informative in this health context, in which the cost of false may be more important than that of false positives. Therefore, according to this curve, given that the model reaches very high precision in some cases, further tuning might be required to improve recall with little sacrifice of precision, as a means of better catching all relevant cases.

This befits TAM, Technology Acceptance Model, and Diffusion of Innovation Theory, which posit that identification of adopters and non-adopters is important in the realization of uptake of technology in healthcare environments (Davis, 1989; Rogers, 2003).

Figure 23 is a typical example of a Receiver Operating Characteristic or ROC Curve, normally used in the evaluation of the performance of a class model. It gives the relationship between the true positive rate against the false positive rate and can be used to show the balance between the correct identification of positives versus that of negatives as positive. An ROC Curve indicates how well a model is capable of distinguishing between classes. In this chart, the red line is the model's performance, while the yellow dashed line is the baseline for the performance, which would be equivalent to random guesses. This latter would be 0.5 AUC. The AUC for this model is 0.55, which is a bit better than a random classification. Thus, this model suffers somewhat in its discriminative power and cannot classify well between classes, such as "Effective" vs. "Not Effective".

The true positive rate on the y-axis shows how well the model captures actual positives, while the false positive rate along the x-axis indicates the share of false alarms. The shape of the curve suggests that the model does not achieve high sensitivity with anything but a high number of false positives, which could be problematic for some healthcare applications. In that respect, the low AUC-ROC score in healthcare regarding the adoption of predictive analytics reflects possible weaknesses in relation to the capability of the model to classify adopters and non-adopters correctly. According to the Diffusion of Innovation Theory by Rogers (2003), this might affect the capability to identify early adopters of technology accordingly. Alternatively, this model would be in need of further tuning or even alternative approaches that will make it perform better, possibly in adjusting the threshold decision or incorporating features.

The figure 24 is a learning curve for XGBoost, plotting the training accuracy (in red) against the cross-validation accuracy in green, as the number of training examples increases. This gives an idea of the performance of this model and provides an insight into whether the model is suffering from overfitting or underfitting, or if there is an optimal balance between bias and variance.

The training score of about 85% is a pretty high ratio, which suggests that this model has fitted the training data quite well. But there's some risk of overfitting too, since it's fitting just a bit too well on the training data and without generalizing on its unseen data. Cross-validation score starts at about 75% and fluctuates down to a final value of around 70%. This generally lower score of cross-validation, as compared to training, is indicative that its performance is not quite as good on data that it has never seen before. This difference in accuracy between training and cross-validation suggests overfitting, in that the model does well on the training data but cannot generalize this performance to new data.

The gap between the lines is essence, this is to say that a large gap, which is depicted between training score and cross-validation score, basically means overfitting; the model performs very low on the validation data compared to the training data. Ideally, these lines should converge closer with a rise in the number of training examples, meaning that the model generalizes well.

The SHAP summary plot on figure 25 shows how different features affect predictions in XGBoost. The x-axis in the plot is labeled with SHAP values, describing the magnitude and direction of each feature's influence on the prediction outcome. The features are ranked by their importance sorted in descending order. Each dot corresponds to an individual instance. Color-coding represents the feature's value, from blue (low) to red (high). Features such as gender and opinions like “There is cultural resistance to adopting new technologies in my hospital” drive the predictions, while features like “How effective are the data management practices” and “How willing are you to implement predictive analytics” have less influence on the model output, which infers that these features play a less influential role in the decision-making process. This visualization could derive which feature is most important to the adoption of predictive analytics in Ghanaian hospitals.

DISCUSSION

The first objective was to investigate the interaction effects between demographic factors and key predictors on the implementation of predictive analytics. The findings revealed that cultural expectations about gender roles could affect professional choices and explains why males are more willing to adopt new technologies. The clinical staff generally are very open to adopt predictive analytics, however, the male component has more predictive power in that job category. This is a very important finding since clinical staff are key employees of the healthcare industry and for that matter their willingness to adopt a new technology is a plus. They form the majority of the staff strength and as a result, their actions would send signal to the minority to follow suit, thus, their adoption of predictive analytics would influence the other category of staff to do same.

The study again revealed that experience in the health sector is a very significant determinant of adoption because professionals with 6-10 years of experience are more likely to adopt predictive analytics use. This means that workers with a moderate level of experience may have attained enough experience to feel confident in adopting new technologies such as predictive analytics. These group of professionals are not too young and also not too old in the profession, thus, an easy target to breach the gap between the most experienced and the inexperienced professionals in the industry to adopt predictive analytics.

The study found St. Edward Hospital more likely to adopt predictive analytics, followed by St. John of God Hospital with St. Elizabeth Hospital as the least likely facility to adopt regardless of the similar IT infrastructure in place. This shows that the cultural and organizational structure of institutions plays a crucial role in the adoption of new technologies. Institutions, therefore, must position themselves in order to not to create barriers to inventions but must rather be open for innovations to improve the operational efficiency and ultimately improve patients’ outcomes.

Comparing the performance of the logistic regression model with that of the extreme gradient boosting in predictive analytics adoption among Ghanaian hospitals using various metrics will help in understanding where relative strength and limitations of each model lie.

Logistic Regression reached the highest accuracy of 91.11% with the best configuration of models against the XGBoost model, standing at an accuracy of 83%. Therefore, logistic regression has been better in classifying instances correctly.

XGBoost demonstrated better precision in identifying "Not Effective" cases with a value of 1.00, implying all the predictions of being a non-adopter were correct. However, its recall was abysmally low at 0.25 for this class, as it missed a number of actual non-adopters, performing poorly in correctly classifying true negatives. Logistic Regression showed better balance between precision and recall for both classes, with lesser variation across classes, which can be said to mean better consistency in the right identification of adopters and non-adopters. While the F1-score is balanced in precision and recall for XGBoost, with an overall less-balanced performance across classes, Logistic Regression works more uniformly across classes. Therefore, it may be considered more reliable for situations in which both classes are of equal importance to identify.

Also, reflected in the learning curve by the high train score and relatively lower cross-validation scores, XGBoost may easily overfit. Often a problem with boosting algorithms is that they are very flexible and tend to memorize training data. On the other hand, Logistic Regression is not likely to overfit since it has fewer parameters; hence, less complex and linearly simple. Logistic regression was also better in the context of generalization performance due to cross-validation; it had more stable results. Considering the models themselves, the XGBoost model showed a cross-validation score of 72.22% on average, while logistic regression models performed at the top during cross-validation checks, thus generalizing well on unseen data.

Logistic Regression has the advantage of being more interpretable since it is linear in nature, with clear coefficients showing the strength of each feature's influence. This can be important in health settings where interpretability may be more critical. XGBoost is far more accurate in many scenarios, but it is also more complex and difficult to interpret since it bases its decisions on nonlinear boundaries.

CONCLUSIONS AND IMPLICATIONS OF THE FINDINGS

In the investigation into interaction effects, it was clear that institutional factors, such as IT infrastructure, interact with demographic factors like gender and prior experience in technology adoption. Further research might extend this analysis by investigating which combinations of individual and organizational factors produce what interaction effects within industries or settings. The paper contributes to the growing literature of machine learning in healthcare through the comparison of the performance of logistic regression against a more sophisticated machine learning algorithm, XGBoost. Logistic regression was better in terms of generalization and consistency, as well as interpretability, compared to XGBoost, while the latter performed well regarding precision for specific classes but was prone to overfitting. These findings form a research foundation to understand the trade-offs among various models in healthcare predictive analytics and could indicate that the performance of simpler models outperforms complex models in specific contexts of healthcare. The study finds that the segment of workers who are moderately experienced, that is, those workers with experience ranging between 6 and 10 years, are more likely to adopt predictive analytics. This might help future research on workforce dynamics and technology readiness, especially focusing on middle-tier professionals who have confidence in implementing new technologies without being obstructively resistant to change due to long-standing routines.

Conflict of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

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