European Journal of Computer Science and Information Technology,13(33),16-29, 2025
Print ISSN: 2054-0957 (Print)
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Impacts of Demographic Factors in Shaping Healthcare Professionals' Perception and Adoption of Predictive Analytics in Ghanaian Hospital Settings

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doi: https://doi.org/10.37745/ejcsit.2013/vol13n331629 Published June 02, 2025

Citation: Mensah CDB and Amanfo BA (2025) Impacts of Demographic Factors in Shaping Healthcare Professionals' Perception and Adoption of Predictive Analytics in Ghanaian Hospital Settings, *European Journal of Computer Science and Information Technology*,13(33),16-29

Abstract: *This study investigated the impact of demographic factors; specifically, age, gender, job experience and job title on health professionals' perception and adoption of predictive analytics in Ghanaian hospital settings. 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. The findings revealed that gender was a significant predictor of adoption, with male healthcare professionals being over twice as likely to adopt predictive analytics as their female counterparts. Other demographic variables, such as age, job title, and years of experience, were not statistically significant. While the presence of IT infrastructure and effective data management systems supported adoption, they were not standalone predictors. The analysis also showed strong model robustness, with high sensitivity and overall classification accuracy. It is therefore recommended that, a universal inclusive training strategy should be adopted to bridge demographic gaps, particularly for less experienced and female staff to foster a culture of innovation focused on improving patient outcomes.*

Keywords: demographic factors, predictive analytics, healthcare professionals, technology adoption, digital health, hospital settings

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INTRODUCTION

In recent years, the global integration of technology across various sectors has significantly transformed how services are delivered, particularly within healthcare. The digital revolution has brought about the rise of advanced tools, such as predictive analytics, which are being utilized to enhance patient outcomes, streamline clinical workflows, and optimize resource allocation. Predictive analytics refers to the use of historical data, statistical algorithms, and machine learning techniques to anticipate future events and support clinical decision-making (Dalen, 2020). This technology enables healthcare professionals to identify at-risk patients, forecast disease outbreaks, and improve overall treatment outcomes. Developed countries have been at the forefront of adopting predictive analytics, with many health systems embedding these tools into everyday clinical practice (Wang et al., 2018). For example, hospitals in the United States and parts of Europe utilize predictive models to manage patient flow, predict hospital readmissions, and allocate ICU beds efficiently. These technologies not only enhance the quality of care but also promote cost-effectiveness and operational efficiency.

In contrast, the implementation of predictive analytics in developing countries, including Ghana, remains emerging. Although the Ghanaian healthcare sector has shown growing interest in adopting modern technological solutions, significant challenges persist (Acheampong, 2012; Govindaraj et al., 1996). These challenges include limited infrastructure, inconsistent data quality, insufficient IT capacity, and a shortage of skilled personnel trained in data science and analytics (Yusif, 2020). Financial constraints also inhibit the procurement and maintenance of analytics systems, which affects the sector's ability to fully harness the benefits of predictive technologies (Yusif, 2020).

Ghana's healthcare system is composed of three main sectors: government-run facilities, quasi-government institutions, and private health providers (Alhassan et al., 2015). Government facilities include teaching and general hospitals that are entirely state-funded. Quasi-government facilities operate privately but receive partial government support, while private health institutions function independently, often offering higher-cost services without government subsidies. The implementation of the National Health Insurance Scheme (NHIS) in 2003 sought to increase accessibility and affordability of healthcare by replacing the out-of-pocket "cash and carry" model with a pre-paid insurance system (Alhassan et al., 2015). This shift has enhanced access to care, but also placed additional strain on facilities needing to improve efficiency and manage resources; gaps predictive analytics could help bridge. Despite these efforts, Ghana's healthcare sector continues to grapple with workforce limitations in health informatics and data analytics. According to Yusif (2020), the shortage of trained data scientists and analytics professionals impedes the development, implementation, and management of predictive analytics systems. Additionally, cultural and organizational resistance, particularly among clinicians unfamiliar with new technologies, further complicates adoption efforts (Appiagyei, 2018). Resistance may stem from skepticism, lack of training, or fear of changes in clinical workflows, thereby creating a need for comprehensive strategies that encourage organizational buy-in and user engagement across all levels; from senior management to frontline healthcare staff.

Given Ghana's unique socio-economic context, exploring how demographic factors such as age, gender, professional experience, and education level shape healthcare professionals' perception and adoption of predictive analytics is crucial. Understanding these dynamics is essential for guiding strategic interventions, policy development, and training initiatives that can facilitate the successful integration of analytics in hospital environments. The present study, therefore, seeks to examine the impacts of demographic variables on healthcare professionals' acceptance and use of predictive analytics in Ghanaian hospital settings. Specifically, this particular study was designed to determine the demographic characteristics of healthcare professionals in Ghanaian Hospitals settings and how demographic variables (e.g., age, gender, job title) affect the adoption and perceived effectiveness of predictive analytics in hospitals. To achieve the objective of the study, the following research questions were posed by the researchers to be answered.

1. What are the dominant demographic characteristics of healthcare professionals in hospitals within the Catholic Diocese of Goaso?
2. How do demographic variables (e.g., age, gender, job title) affect the adoption and perceived effectiveness of predictive analytics in hospitals?

THEORETICAL FRAMEWORK

Theories play a crucial role in research studies, providing a structured framework for understanding phenomena, guiding the research process, and linking the study to existing knowledge. Theories help in formulating research questions, hypotheses, and determining variables of interest. They offer a lens through which the researcher can view the problem, guiding the design and methodology of the study. According to Creswell and Creswell (2018), a theoretical framework acts as a blueprint, shaping the entire research process and helping to maintain consistency and focus. Theories explain how and why certain phenomena occur. By relying on theoretical constructs, researchers can interpret data within a larger context, thus enhancing the explanatory power of their findings. As Neuman (2014) notes, theories serve as abstract tools that allow researchers to make sense of complex social realities. A sound theoretical framework enables the prediction of outcomes in similar settings, enhancing the generalizability of the findings. Theories can be used to anticipate behaviors, relationships, or patterns that might emerge under specific conditions (Babbie, 2020). Theories connect new research to the broader body of existing knowledge. They ensure continuity in scholarly discourse and prevent redundancy in research. Kerlinger and Lee (2000) emphasize that theoretical frameworks ensure the accumulation of knowledge by aligning new studies with past research.

By grounding research in established theoretical frameworks, studies gain academic rigor and credibility. This not only enhances the trustworthiness of findings but also aids in peer acceptance and publication (Maxwell, 2013). Theories are fundamental in ensuring that research is coherent, logically structured, and rooted in scholarly tradition. They not only guide the research process but also enrich the interpretation, application, and dissemination of findings.

A theoretical lens useful for understanding healthcare professionals' adoption of predictive analytics is the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). This theory was therefore adopted by the researchers to explain the related concepts in the study.

Figure 1 shows a diagram illustrating the Unified Theory of Acceptance and Use of Technology (UTAUT) which outlines the factors that affect how technology is accepted and used by individuals. This model posits that four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions determine an individual's behavioral intention to use technology, which in turn predicts actual usage. Moderating variables such as age, gender, experience, and voluntariness of use further influence these relationships. In healthcare settings, this model has been widely used to evaluate how practitioners perceive and engage with new technologies, offering a robust framework for exploring the demographic dynamics behind technology adoption.

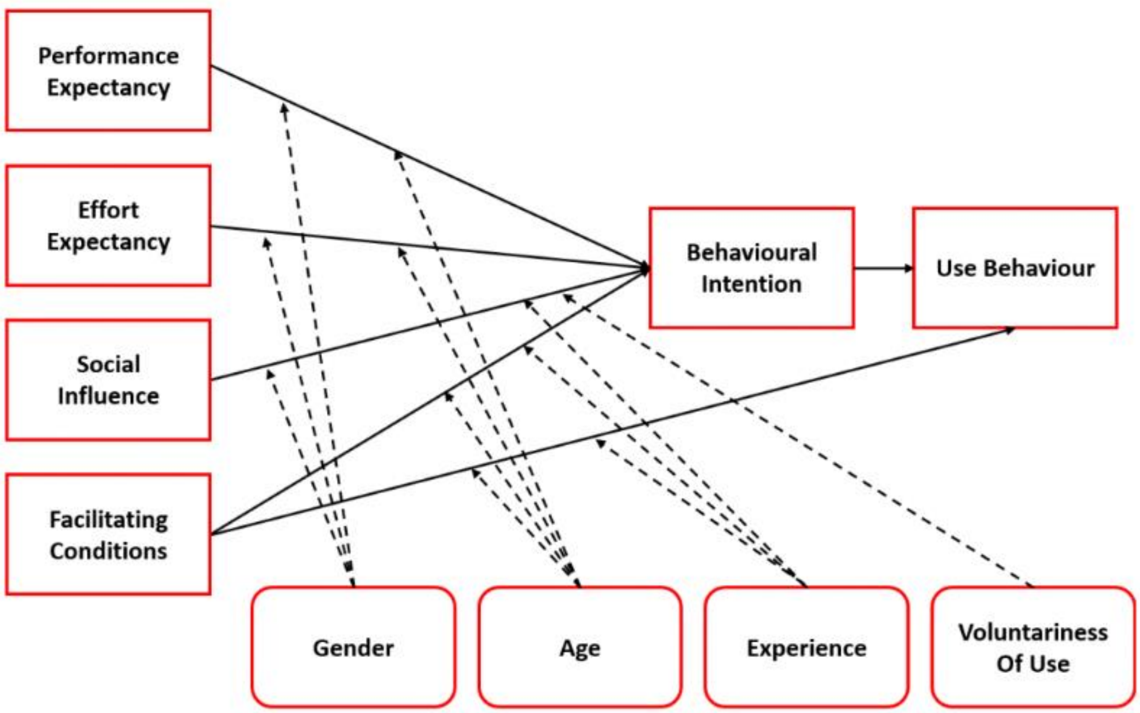

Figure 1: Graphical Representation of the Unified Theory of Acceptance and Utilization of Technology

MATERIALS AND 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. 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

This section presents the results and findings on the two research questions for the study.

Research Question 1:
What are the dominant demographic characteristics of healthcare professionals in hospitals within the Catholic Diocese of Goaso?

This particular research question sought to analyze the demographic composition of healthcare professionals within Catholic hospitals in the Goaso Diocese. Presented in Table 1 are the results of the study.

Table 1: Descriptive Statistics of the Various Variables in the Dataset

	Freq.	Percent	Cum.
Gender			
Female	43	47.78	47.78
Male	47	52.22	100.00
Age			
Below 34 years	42	46.67	46.67
35-54 years	34	37.78	84.44
Above 55 years	14	15.56	100.00
Job Title			
Administrative Staff 1	16	17.78	17.78
Doctor/Nurse/Midwife	53	58.89	76.67
Other Clinical Staff	21	23.33	100.00
Where do you work			
St. Edward Hospital	30	33.33	33.33
St. Elizabeth Hospital	30	33.33	66.67
St. John of God Hospital	30	33.33	100.00
How would you rate the current IT infrastructure in your hospital			
Poor	15	16.67	16.67
Average	27	30.00	46.67
Good	48	53.33	100.00
How effective are the data management processes in your hospital			
Ineffective	10	11.11	11.11
Neutral	19	21.11	32.22
Effective	61	67.78	100.00
Total	90	100.00	

From Table 1: on the issue of Gender, it is shown that there is an almost even representation of males and female respondents with 47 males and 43 females.

Majority of the respondents, as shown in Table 1, are below the ages of 34 representing 46.67%, followed by 35-54 age brackets with 37.78% representation. Respondents above 55 years (15.56%) were in the minority.

In the healthcare industry, the clinical staff who are made up of the Doctors, Nurses, Midwives, officers and technicians from Laboratory, Pharmacy, and other areas in the hospital constitute the majority. Therefore, the clinical staff together represented 82.22% while the Administrative and supporting staff constituted 17.78% of the respondents.

Majority of the respondents, 50%, as shown in Table 1 had worked in the healthcare industry for less than 5 years. Those who had worked between 6 to 10 years were 27.78% while those who had more than 11 years' experience constituted 22.22%.

Regarding the opinion on the state of IT infrastructure in the various hospitals, 53.33% of the respondents rated it as good, 30% rated it as average and 16.67% rated it as poor. The effectiveness of the data management system in the hospitals was rated 67.78% as effective, 21.11% as neutral and 11.11% as ineffective.

Table 2: Multicollinearity Test

	VIF
Years of Experience in Healthcare	1.636
Age	1.621
There is cultural resistance to adopting new technologies in my hospital	1.52
How would you rate the effectiveness of the electronic health records system	1.451
There is cultural resistance to adopting new technologies in my hospital	1.411
How effective are the data management processes in your hospital	1.41
Does your hospital use electronic health records (EHRs)	1.403
Have you received any training in predictive analytics related to healthcare	1.36
Where do you work	1.322
How would you rate the quality of the training	1.289
How do you assess your familiarity with predictive analytics	1.238
Gender	1.179
How willing are you to implement predictive analytics in your daily work	1.173
What type of training is required for predictive analytics	1.137
Job title	1.125

From Table 2, results of the multicollinearity test by means of the VIF show that all the variables have VIF values below the normally accepted cutoff threshold of 10, hence there is no problem of multicollinearity. Multicollinearity is a situation where the independent variables in a regression model are highly correlated to each other, a fact that always leads to distorted estimates of the regression coefficients (Gujarati & Porter, 2009). In this regard, the respective low VIF values of 1.125 to 1.636 suggest that the variables tested are not highly interrelated; thus, the assurances of the reliability of the results of the regression model are warranted.

The highest VIF value, 1.636, comes from the variable "Years of Experience in Healthcare," whereas the second closest is the variable "Age" with a value of 1.621. While these values illustrate a modest correlation, these are within the range of acceptability, which is a good indication that valid interpretations could be made regarding their effects on the dependent variable. Based on Human Capital Theory, variables such as years of experience and age are considered crucial determinants in ascertaining the level of capacity that health professionals possess in working effectively with predictive analytics and IT infrastructure. These VIF values prove that these human capital variables can be interpreted without issues of multicollinearity. Other variables such as "How willing are you to implement predictive analytics" and "Have you received any training," with low VIFs of 1.173 and 1.36, respectively, further suggest the low risk of distorted interpretations in understanding those factors that influence the adoption of predictive analytics in Ghanaian hospitals. This also aligns with the Technology Acceptance Model-TAM by Davis 1989, where some of the key factors that affect acceptance and utilization of new technologies like predictive analytics include things like willingness and training.

From this, it follows that the absence of multicollinearity in this analysis actually lends credence to the soundness of the regression model and reinforces confidence in the interpretation of the relationships

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between the variables. This ensures, therefore, that the study can be relied upon to ascertain a healthcare policy promulgated in the interest of improving IT infrastructure and predictive analytics at Ghanaian hospitals.

Research Question 2:
How do demographic variables (e.g., age, gender, job title) affect the adoption and perceived effectiveness of predictive analytics in hospitals?

This research question was intended to ascertain how health staff demographic characteristics such as age, gender, job title and work experience affect their acceptance and adoption of predictive analytics technology in their hospitals.

Table 3: A logistic regression with two different models (with and without control variables)

	Model 1	Model 2
	AOR (Std. Err)	AOR (Std. Err)
Gender		
Female	Reference	
Male	2.463***(0.776)	
Age		
Below 34 year	Reference	
35-54 years	-0.729 (1.753)	
55 years and Above	-1.420 (1.481)	
Job Title		
Administrative Staff 1	Reference	
Doctor/Nurse/Midwife	0.740 (1.261)	
Other Clinical Staff	0.532 (1.400)	
Years of Experience in Healthcare		
Below 5 years	Reference	Reference
6-10 years	1.430 (1.168)	1.019 (0.950)
11 years and Above	-0.122 (1.275)	-0.120 (0.788)
Where do you work		
St. Edward Hospital	Reference	Reference
St. Elizabeth Hospital	-2.489** (1.211)	-1.572 (0.959)
St. John of God Hospital	-1.721 (1.298)	-0.817 (1.058)
How would you rate the current IT infrastructure in your hospital		
Poor	Reference	Reference
Average	1.438 (2.425)	2.015 (1.808)
Good	0.827 (1.638)	0.449 (1.132)
How effective are the data management processes in your hospital		
Ineffective	Reference	Reference
Neutral	0.183 (1.542)	0.0471(1.643)
Effective	-1.599 (1.429)	-0.738 (1.545)
If yes, how would you rate the effectiveness of the electronic health records system		
Ineffective	Reference	Reference
Neutral	-4.739 (3.403)	-3.997* (2.155)

Effective	-2.150 (1.903)	-2.130 (1.496)
How do you assess your familiarity with predictive analytics		
Not familiar at all	Reference	Reference
Moderately familiar	-2.056* (1.199)	-1.439* (0.812)
Very familiar	-0.523 (1.792)	0.128 (1.177)
Have you received any training in predictive analytics related to healthcare		
No	Reference	Reference
Yes	-0.983 (1.007)	-0.944 (0.725)
How willing are you to implement predictive analytics in your daily work if you get the required resources and training		
Not willing	Reference	Reference
Very willing	0.228 (1.288)	-0.292 (0.944)
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	-2.216 (1.607)	-1.793 (1.271)
Workshops, On-the-job training, Certification programs	-0.792 (2.453)	-1.296 (1.715)
Workshops, Online courses, On-the-job training, Certification programs	-0.710 (1.471)	-0.995 (1.373)
"There is cultural resistance to adopting new technologies in my hospital"		
Disagree	Reference	Reference
Neutral	1.224 (2.575)	0.638 (1.456)
Agree	4.233** (1.763)	2.275** (0.926)
"There are organizational barriers that hinder the implementation of predictive analytics in my hospital"		
Disagree	Reference	Reference
Neutral	-5.779*** (1.667)	-4.566*** (1.018)
Agree	-1.779 (1.494)	-1.407 (0.885)
_cons	6.923** (3.381)	7.083** (2.786)
N	90	90
r2		

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

Results of the logistic regression, as shown in Table 3, test drivers of willingness to adopt predictive analytics in Ghanaian hospitals using two models-one without and one with control variables. This therefore establishes a platform on which the theory behind the vital variables shall be drawn upon for adopting predictive analytics. Therefore, it comes out that gender is one of the more significant predictors, while males are 2.463 times more willing to implement predictive analytics than females.

By age group, healthcare professionals in the age brackets 35–54 years old and above 55 years did not have a significant difference in willingness to adopt as compared to those below 34 years old.

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Job title and years of experience are all not statistically significant. Factors at the hospital level also do not have so much effect on willingness to use. However, the overall perceived usefulness has a positive effect.

Table 4: Diagnostic and Robustness Check

<table>
<tr><th>Metrics</th><th>Model 1
(With control variables)</th><th>Model 2
(Without control variables)</th></tr>
<tr><td>Confusion Matrix</td><td><table><tr><td>67</td><td>9</td></tr><tr><td>3</td><td>11</td></tr></table></td><td><table><tr><td>66</td><td>9</td></tr><tr><td>4</td><td>11</td></tr></table></td></tr>
<tr><td>Sensitivity</td><td>95.71%</td><td>94.29%</td></tr>
<tr><td>Specificity</td><td>55.00%</td><td>55.00%</td></tr>
<tr><td>Positive predictive value</td><td>88.16%</td><td>88.00%</td></tr>
<tr><td>Negative predictive value</td><td>78.57%</td><td>73.33%</td></tr>
<tr><td>Correctly classified</td><td>86.67%</td><td>85.56%</td></tr>
</table>

The results in Table 4 depict the diagnostic and robustness checks for two logistic regression models, with and without control variables, which analyze factors that influence the adoption of predictive analytics in Ghanaian hospitals. These metrics provide a view of the predictive performance of the models and thus provide the bases upon which to judge their reliability and accuracy. The sensitivity of correctly identifying those willing to adopt predictive analytics is high for both models, at 95.71% and 94.29%, respectively. This may imply that both models are quite sensitive in identifying the bulk of healthcare professionals who will apply predictive analytics. Sensitivity is crucial in healthcare because it ensures that adopters of new technologies are detected, thus having great implications for organizational readiness and planning.

Specificity the number of correct identifications of those not willing to adopt predictive analytics-is rather low: 55% for both models. The lower specificity reflects greater chance that the models will misclassify some of the people as willing adopters. This finding chimes with the Diffusion of Innovation Theory by Rogers 2003, purporting that not everyone is an early adopter of any innovation, and the relatively lower specificity of the models may reflect the complexity of individual and organizational barriers to adopting predictive analytics.

Positive predictive value and negative predictive value further illustrate the performance of the models. With both models, the PPV stands at approximately 88%, which proves that the majority of the predicted adopters are actually willing to implement predictive analytics. On the other hand, the NPV is a bit lower for Model 2, standing at 73.33% compared to Model 1, at 78.57%, which stands to reason that with control variables, the model did a somewhat better job in predicting true negatives. This also aligns with TAM, which postulates that individual traits and external factors are important in the adoption of technologies, represented through the control variables.

The final aspect is that both models' evidence very high overall classification accuracy: Model 1 correctly classified 86.67% of cases, while Model 2 came in at 85.56%. These findings would thus suggest that though the inclusion of control variables raises the level of performance a little, both models are generally robust and reliable in respect to predicting the adoption of predictive analytics in Ghanaian hospitals.

DISCUSSION

The descriptive analysis of demographic data (Table 1) revealed that male health professionals slightly outnumber females across the three participating hospitals. This gender distribution, coupled with the relatively youthful profile of most respondents, suggests a workforce that may be more open to embracing technological innovations such as predictive analytics. This observation aligns with the findings of Venkatesh et al. (2003), who argue that younger individuals tend to exhibit higher technology acceptance levels due to greater exposure to digital tools in their formative years.

The data further showed that the majority of respondents were clinical staff with fewer than five years of work experience. While this reflects a potentially adaptable workforce, their limited professional exposure could act as a barrier to rapid adoption of complex technologies. According to the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness are primary determinants of user acceptance of new technology (Davis, 1989). Less experienced professionals may lack the contextual knowledge or confidence needed to effectively engage with such systems unless they are adequately supported through training and mentorship (Holden & Karsh, 2010).

All three hospitals; St. John of God, St. Elizabeth, and St. Edward were equally represented, and respondents generally reported the presence of a functioning IT infrastructure, electronic health records (EHRs), and data management systems. These conditions create a conducive environment for implementing predictive analytics. Prior studies have emphasized the critical role of robust technological infrastructure in facilitating digital health transformations (Kruse et al., 2016). However, as observed in this study, the mere presence of IT systems is not sufficient; user engagement and belief in the value of the technology remain key. This finding supports earlier observations by Boonstra and Broekhuis (2010), who argued that successful technology adoption in healthcare often hinges more on organizational culture and user readiness than on infrastructure alone. It also suggests that Ghanaian hospitals, particularly mid-sized facilities, are increasingly establishing the digital groundwork necessary to support data-driven innovations.

Assessing the influence of demographic variables on the adoption predictive analytics, it was found that gender had a statistically significant impact, with males being 2.463 times more likely to adopt predictive analytics than females. This echoes findings by Venkatesh and Morris (2000), who noted gender-based differences in perceived ease of use and intention to use IT systems. Such disparities may stem from socio-cultural factors that influence technology confidence levels among women in professional settings. Hence, while involving males as change agents might facilitate early adoption, deliberate strategies must be designed to build the confidence and digital competence of female staff to ensure equitable engagement.

In contrast, age, job title, and years of experience were found to be statistically insignificant predictors of adoption willingness. This is particularly noteworthy, as it challenges assumptions in earlier literature suggesting that older staff or those in non-technical roles are more resistant to adopting healthcare technologies (Chau & Hu, 2002). The findings suggest that, with adequate training and perceived value, healthcare professionals in Ghana can embrace innovations irrespective of age or role, reinforcing the TAM’s emphasis on perception rather than demographic predispositions.

CONCLUSIONS AND IMPLICATIONS TO PRACTICE

This study examined the impact of demographic factors on healthcare professionals' adoption and perception of predictive analytics in hospital settings across three hospitals in Ghana. The findings reveal that individual perceptions of usefulness, especially when supported by training and institutional commitment, are the most critical drivers of adoption intent, rather than structural or hierarchical factors such as job title or the quality of IT infrastructure. Among the demographic variables, gender emerged as a significant influence, with male professionals showing a higher likelihood of adopting predictive analytics than their female counterparts. This finding suggests that cultural and social expectations may shape adoption behaviors, underlining the importance of incorporating demographic variations, particularly gender roles into future studies of technology adoption in healthcare and other sectors. Although Ghanaian hospitals are becoming increasingly equipped with IT infrastructure, this alone does not guarantee widespread adoption. Instead, institutional factors such as infrastructure appear to interact with demographic variables, like gender and prior technological experience, to influence adoption outcomes. These interaction effects point to a complex ecosystem where individual and organizational characteristics must be understood in tandem.

Given that neither infrastructure quality nor job title significantly influenced professionals' intent to adopt predictive analytics, the study recommends a universal training and implementation strategy rather than a tiered or role-based approach. Such a strategy would ensure that all staff especially less experienced and female professionals are adequately equipped to participate in digital innovation initiatives. Hospital administrators and policymakers should focus on creating a culture of innovation that prioritizes outcome improvement over role-based barriers. This includes actively working to remove institutional and perceptual obstacles that disproportionately affect certain demographic groups, thereby enabling more inclusive and effective adoption of predictive technologies.

In sum, this study contributes to the growing body of literature on digital transformation in healthcare by highlighting the importance of demographic and institutional interplay in technology adoption. Future research should continue to explore which specific combinations of individual and organizational factors yield the most effective outcomes across diverse settings and industries. These findings contribute to the understanding of technology adoption in developing healthcare systems and offer actionable insights for policymakers and hospital administrators in Ghana and similar contexts.

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