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Influence of Demographic Characteristics on Health Workers' Acceptance of Biometric-Controlled Health Informatics Systems: Evidence from Selected Regional Referral Public Hospitals in Uganda

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The integration of biometric technology into health informatics promises improved security and efficiency in healthcare delivery, yet its success hinges on end-user acceptance, particularly in low-resource settings where health workers' attitudes and experiences may differ markedly from those in high-income contexts. While demographic factors such as age, gender, education, and professional experience are known to influence technology adoption more broadly, their specific impact on health workers' acceptance of Biometric Controlled Health Informatics (BCHI) in Ugandan public hospitals remains underexplored. The study therefore aimed to examine how these key demographic variables shape health workers' acceptance of BCHI, using the Technology Acceptance Model (TAM) as the guiding theoretical framework. A quantitative, cross-sectional design was employed, involving 244 clinical and non-clinical health workers from two regional referral hospitals in Uganda, with data collected through a structured, self-administered questionnaire that measured core TAM constructs including attitude, actual usage, perceived usefulness, perceived ease of use, and behavioral intention; the instrument demonstrated good reliability (Cronbach's α 0.885–0.920). Multiple linear regression analyses were then used to assess the unique predictive power of each demographic factor on the TAM constructs. The findings revealed that gender and education level were significant predictors of BCHI acceptance, whereas age and years of professional experience were not. Male health workers reported less favorable attitudes, lower perceived usefulness and ease of use, and reduced actual usage compared to their female counterparts, while Certificate/Diploma-qualified staff showed the highest acceptance across most constructs and Bachelor's degree holders consistently reported lower acceptance, especially for perceived ease of use. In conclusion, acceptance of BCHI among Ugandan health workers is not uniform but is distinctly patterned by gender and educational background, underscoring the need for differentiated implementation strategies, tailored communication and training for male staff and degree-holding cadres, and deliberate use of Certificate/Diploma-level staff as champions to support a more effective, context-sensitive rollout.

Keywords: Biometric technology, Technology acceptance, Health informatics, Demographic factors, Uganda.

1 Introduction

The integrity of medical records is fundamental to safe and effective healthcare delivery [1]. In Uganda, as in many healthcare systems around the world, protecting medical records from unauthorised access and tampering is a critical challenge with direct consequences for patient safety. Documented incidents, such as the case of newborn swapping at Mulago National Referral Hospital linked to the illicit alteration of medical documents, show the severe risks posed by weak identity verification and access control systems [2]. Such breaches facilitate medical fraud, compromise clinical decision-making, and erode public trust in healthcare institutions. Biometric controlled health informatics (BCHI) systems embed fingerprint, facial recognition or other biometric sensors into electronic health record platforms to streamline patient identification; secure data access, and improve service delivery. Medical records are crucial for maintaining

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a patient's health history, documenting treatments, tracking progress, and ensuring continuity of care [3]. To maintain patient confidentiality and privacy, access to these records is typically restricted to authorised healthcare providers [4]. Biometrics, which encompasses unique physical or behavioural characteristics, offers a method for individual identification [5]. These identifiers include physiological traits such as the face, fingerprint, iris, retina, hand geometry, and ear shape, as well as behavioural traits such as signature, gait, speech, and handwriting [5,6]. Thus, the integration of biometric systems into healthcare informatics represents a transformative frontier in healthcare delivery, promising to enhance security, streamline patient identification, and improve the accuracy of health records [7,8,9]. Biometric technologies, which authenticate individuals based on their unique physiological and behavioural characteristics such as fingerprints, iris patterns, or facial recognition, offer a robust alternative to traditional identification methods which are prone to error and fraud [10,5,11]. These systems can safeguard sensitive patient data, ensure better linkage of medical information to the correct individual, and control access to critical healthcare applications and physical areas, thereby forming a cornerstone of modern, secure health informatics infrastructure [12, 13,14].

However, the successful deployment and efficacy of any technological innovation in healthcare are fundamentally contingent upon its acceptance by the end-users, who are the health workers who interact with systems daily [15,16]. As noted by [17], technology acceptance is deeply influenced by the perceptions and attitudes of its users [17]. In hospitals, where workflow efficiency and data integrity is paramount, user resistance can significantly undermine the potential benefits of even the most advanced systems [18]. Demographic variables such as gender, ethnicity, education, and age play a significant role in shaping technology acceptance [19,20]. For instance, studies in other sectors indicate that younger individuals may exhibit higher familiarity and comfort with new technologies, while differences based on professional specialisation can affect perceived usefulness and ease of use [21]. Within healthcare, these demographic factors may intersect with unique professional norms, concerns about patient privacy, and the high-stakes clinical environment, creating a complex landscape for biometric adoption [22].

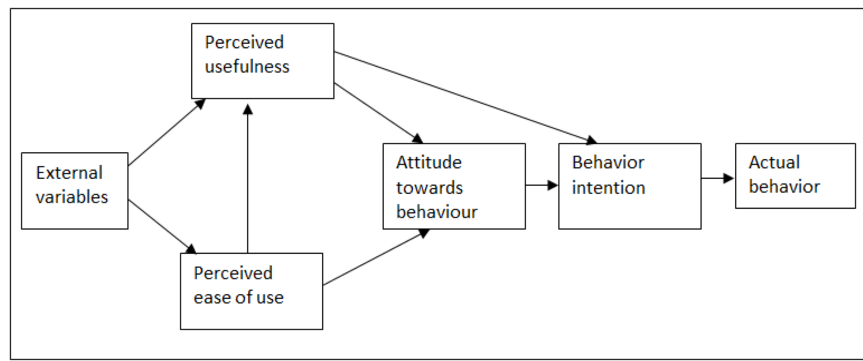

Fig. 1. Technology Acceptance Model (TAM), adopted for the study

This study is grounded in the Technology Acceptance Model (TAM), the predominant theoretical framework for investigating individual acceptance of information systems as show in Figure 1 above [23]. Originally adapted from the Theory of Reasoned Action [24], TAM posits that an individual's behavioural intention to use a technology is primarily determined by their perceived usefulness (the degree to which a person believes using the system will enhance their job performance) and perceived ease of use (the degree to which a person believes using the system will be free of effort) c. In the context of this research, these core TAM constructs – Perceived Usefulness, Perceived Ease of Use, and the resulting Behavioural Intention – operationalise the dependent variable: Acceptance of Biometric Controlled Health Informatics (BCHI). The model provides the essential mechanism to investigate this study's central question: how the independent variables, namely demographic characteristics of health workers in Ugandan public hospitals, influence these foundational perceptions and, consequently, their overall acceptance of the biometric system. By applying TAM, the study moves beyond merely documenting acceptance levels to explaining the psychological and contextual pathways through which individual differences shape technology adoption in a critical healthcare setting.

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In several African countries, biometric systems are being implemented to enhance various aspects of healthcare administration. For instance, in Kenya and Uganda, biometric technology is utilised to monitor healthcare worker attendance in rural settings, aiming to improve accountability and service delivery [25]. Concurrently, nations such as Ghana, Rwanda, and Zambia have adopted biometric systems for health insurance enrolment and identity verification. This application seeks to prevent fraudulent enrolment and streamline administrative processes, thereby increasing the efficiency of health insurance schemes [26]. Despite the clear importance of user demographics, research specifically examining their influence on acceptance of biometric systems among health workers in Uganda remains sparse. Most studies on biometrics in healthcare have focused on technical feasibility, accuracy, or broad surveys of patient attitudes, leaving a gap in understanding the healthcare professional's perspective [27].

Ugandan public hospitals have documented cases of medical record tampering [2]. Such breaches compromise patient safety, enable medical fraud, and erode institutional trust. Biometric authentication technology offers a potential solution through its unique ability to link digital identities to immutable physiological characteristics, making unauthorised access extremely difficult. The Ugandan Ministry of Health has recognised this potential, with Dr Tumwesigye endorsing fingerprint biometrics for tracking antiretroviral therapy patients as part of the national e-health strategy [28]. However, implementation success depends fundamentally on user acceptance. Research consistently identifies healthcare professional resistance as a critical barrier to biometric system adoption [29,30]. Concerns about privacy invasion, data security, and technological complexity drive this reluctance [31,32]. While studies have examined the technical feasibility of biometrics in healthcare and broad patient attitudes, there is a scarcity of research specifically investigating how the demographic profiles of healthcare professionals influence their acceptance of these systems [27]. The purpose of this study is to investigate the influence of demographic factors on the acceptance of Biometric-Controlled Health Informatics (BCHI) among health workers in Ugandan public hospitals. The study is grounded in the Technology Acceptance Model (TAM), which provides a framework for understanding how perceptions of usefulness and ease of use drive behavioural intention and actual use [23]. The primary research question guiding this inquiry is how do key demographic characteristics (age, gender, educational level, professional cadre, and years of experience) influence health workers' acceptance of biometric-controlled health informatics systems in Ugandan public hospitals?

2 Materials and methods

This research employed a quantitative, correlational study design to assess the influence of demographic factors on the acceptance of Biometric Controlled Health Informatics (BCHI). The design was embedded within a larger sequential explanatory mixed-methods framework, with this specific objective addressed by the initial quantitative phase [33]. The study protocol received full ethical approval from the Unicaf University Research Ethics Committee (UREC), the Uganda National Council for Science and Technology (UNCST), and the Uganda National REC. Prior to participation, all subjects provided written informed consent, having been fully informed of the study's purpose, their right to withdraw at any time without consequence, and the measures in place to ensure the confidentiality and anonymity of their data. The source population was defined as all clinical and non-clinical health workers employed at two public regional referral hospitals in Uganda: Gulu Regional Referral Hospital and Soroti Regional Referral Hospital. Eligibility criteria included being a formally employed health worker (clinical or non-clinical) at one of the two study sites during the data collection period. There were no exclusion criteria based on department or role, as the aim was to capture a holistic view of the hospital workforce. Participant selection aimed for a representative sample to allow for generalisation of findings related to demographic influences [34].

A systematic random sampling technique was applied to obtain a probability sample from the available staff lists (sampling frames) provided by the human resources departments of both hospitals [35]. This method ensured every eligible health worker had a known, equal chance of selection, minimising selection bias. The sample size was determined a priori using a precision-based formula for a finite population [36], with inputs of a 95.5% confidence level (Z=2.005), maximum variability (p=0.5), and a desired precision (e) of 0.02. This calculation yielded a target sample of 127 participants from Gulu RRH and 117 from Soroti RRH, for a total of N=244.

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The primary research instrument was a structured, self-administered questionnaire [37,38]. The questionnaire comprised several sections. Section A collected data on the independent demographic variables: age (continuous), gender (categorical), highest educational level (ordinal), years of professional experience in healthcare (ordinal), and professional cadre. Section D measured the dependent variable (BCHI acceptance) using a modified version of the established Technology Acceptance Model (TAM) questionnaire [23, 39]. This section contained multi-item scales measuring Perceived Usefulness (4 items), Perceived Ease of Use (3 items), and Behavioural Intention to Use (2 items). All items used a five-point Likert response format from 'Strongly Disagree' to 'Strongly Agree' [40]. Data collection was conducted on-site at the two hospitals. Questionnaires were distributed to selected participants and collected upon completion, ensuring a high response rate and data integrity.

All quantitative data were prepared and analysed using IBM SPSS Statistics (Version 29). The analysis plan for this objective was formulated as follows. First, descriptive statistics (frequencies, percentages, means, and standard deviations) were computed to describe the sample's demographic composition and summarise the scores on the acceptance scales. Second, inferential statistics were employed to test the relationships between demographics and acceptance. Independent samples t-tests and one-way Analysis of Variance (ANOVA) were used to compare mean acceptance scores across categorical demographic groups (e.g., gender and education categories). Correlation analysis (Pearson's or Spearman's) assessed the relationship between continuous/ordinal variables (age, experience) and acceptance scores. Finally, a standard multiple linear regression analysis was conducted as the primary model to evaluate the unique contribution of each demographic factor while controlling for the others, assessing overall model fit (R^2) and the significance of individual predictors (β coefficients) [41]. the quantitative analysis identified statistical relationships, the sequential design allowed for subsequent qualitative data to be used interpretively. [42, 43, 44].

3 Results

The study findings are structured to first establish the robustness of the measurement instruments and the distributional properties of the data. It then provides a demographic profile of the participant before regression analyses. The analyze examine the influence of key demographic factors namely age, gender, and education level on health workers' acceptance of Biometric Controlled Health Informatics (BCHI), as measured by the core constructs of the Technology Acceptance Model: which are Perceived Usefulness, Perceived Ease of Use, Attitude, Actual Usage, and Behavioral Intention.

Reliability refers to the consistency, stability, and repeatability of a measurement instrument or procedure [45] indicating that repeated administration of the same instrument should yield consistent results. In this study, the reliability of the five key constructs used to measure the influence of demographic factors on the acceptance of Biometric Controlled Health Informatics (BCHI) among health workers was rigorously assessed to ensure the validity of the quantitative findings.

Table 1. Cronbach Reliability Statistics Results

Construct	No. of Items	Cronbach's α
1. Perceived Usefulness	5	.920
2. Perceived Ease of Use	6	.885
3. Attitude	5	.893
4. Actual Usage	6	.891
5. Behavioral Intention	5	.919

This reliability analysis confirms that all five constructs measuring health workers' acceptance of Biometric Controlled Health Informatics (BCHI) systems in Ugandan public hospitals show strong to excellent internal consistency. The Cronbach's alpha coefficients, ranging from .885 to .920, all comfortably exceed the conventional threshold of .70 [46], indicating the scales are reliable for use in subsequent analyses.

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Perceived Usefulness (α = .920) and Behavioral Intention (α = .919) exhibit excellent reliability. These are core constructs in technology acceptance models and are central to the study's second research question, which investigates the relationship between personality traits and BCHI acceptance. Their high reliability ensures that measurements of health workers' perceptions about the utility of BCHI systems and their actual intention to use them are stable and consistent.

Perceived Ease of Use (α = .885), Attitude (α = .893), and Actual Usage (α = .891) all demonstrate good reliability. These scales are crucial for understanding the practical and psychological barriers to adoption highlighted in the problem statement, such as user reluctance, privacy concerns, and the challenges of integrating new technology into clinical workflows. The reliable measurement of Actual Usage is particularly important for exploring the influence of demographic factors like experience, as outlined in the third research question.

The results on the normality assessment indicate that all five variables meet the assumptions required for parametric statistical analysis. As presented in Table 1, the skewness values for the variables range from -0.215 to 0.112. According to established psychometric guidelines, skewness values between -0.5 and +0.5 are generally considered acceptable for assuming a normal distribution in social science research [47, 48]. This aligns with recent methodological research, which confirms that for most statistical models in the health sciences, the effect of skewness is negligible within this range [49]. In our data, Attitude shows minimal positive skewness (0.112), and Perceived Easiness exhibits slight negative skewness (-0.215). The skewness values for Actual Usage (-0.029) and Perceived Usefulness (0.009) approach perfect symmetry, while Behavioural Intention demonstrates acceptable negative skewness (-0.101). Regarding kurtosis, all variables display negative values ranging from -0.157 to -0.846. Field (2024) notes that kurtosis values within approximately ±1.0 are generally acceptable for most parametric analyses, a guideline supported by Hatem et al. (2022), who emphasise that such minor deviations from mesokurtosis (kurtosis = 0) do not significantly compromise the validity of standard tests like ANOVA or linear regression [50, 51]. The obtained values fall well within this acceptable range, indicating slightly flatter-than-normal distributions, which is a common and manageable pattern in applied research [52]. Furthermore, with an adequate sample size (N=244), the central limit theorem ensures the robustness of parametric inference even when mild deviations in distributional shape are present, reinforcing the suitability of these variables for subsequent analysis [49].

The normality of all five variables Attitude, Actual Usage, Perceived Usefulness, Perceived Ease of Use, and Behavioural Intention toward Biometric-Controlled Health Informatics was assessed to validate assumptions for parametric analysis. This statistical evidence was shown by the normality probability plots, in which the observed data points closely followed the diagonal reference line, confirming the absence of significant skew or outliers. With an adequate sample size (N = 244) and the assurances afforded by the Central Limit Theorem, the robustness of parametric inference is further supported. Consequently, these variables are deemed suitable for subsequent parametric regression analysis.

Table 2. Participant Demographics

Characteristic	Categories	Frequency (n)	Percentage (%)	Mean(SD)
District / Hospital	Gulu	127	52.0	
	Soroti	117	48.0	
Gender	Female	127	52.0	
	Male	117	48.0	
Age (Years)				**38.02 (9.239)**
Education Level	Basic	10	4.1	
	Certificate/Diploma	98	40.2	
	Bachelor's Degree	108	44.3	
	Master's Degree	23	9.4	
	PhD	5	2.0	
Years Employed	Less than 1 year	14	5.7	
	1-5 years	62	25.4	
	5-10 years	94	38.5	

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	10-15 years	40	16.4	
	15+ years	34	13.9	

The demographic characteristics of the 244 participating health workers from Gulu and Soroti Regional Referral Hospitals are presented in Table 1. The sample was nearly evenly split by hospital location, with 52.0% (n=127) from Gulu and 48.0% (n=117) from Soroti, and by gender, with 52.0% female and 48.0% male participants. The average age of respondents was 38.02 years (SD = 9.239). In terms of educational attainment, the majority held a post-secondary qualification: 40.2% possessed a certificate or diploma, 44.3% held a bachelor’s degree, and 11.4% had completed postgraduate studies (master’s or PhD). Only 4.1% reported a basic level of education as their highest. Regarding professional tenure, the sample were experienced, with most health workers (38.5%) having served for 5-10 years. A combined 68.8% had more than five years of service, while a smaller proportion (5.7%) had been employed for less than one year. This profile indicates a sample of mature, educated, and experienced health professionals, providing a solid foundation for examining how these demographic factors relate to the acceptance of biometric technology.

The regression analysis reveals which demographic factors significantly predict health workers' overall attitude toward Biometric Controlled Health Informatics (BCHI). Gender emerged as a significant predictor (β = -.180, p = .005), indicating that, compared to females, male health workers reported a significantly less favourable attitude toward the technology, holding other factors constant. Educational level also showed significant effects, with the bachelor's degree category serving as the reference. Health workers with a basic education level (β = .138, p = .030), a certificate/diploma (β = .214, p = .002), and a master's degree (β = .169, p = .010) all reported significantly more positive attitudes than those holding a bachelor's degree. Notably, attitudes among PhD holders did not differ significantly from Bachelor's degree holders. In contrast, age was not a statistically significant predictor of attitude in this model (β = .044, p = .495). Collectively, these results suggest that professional gender and specific educational backgrounds are key demographic dimensions influencing acceptance, while age, within this sample, does not appear to be a determining factor.

Table 3. Regression Analysis of Demographic Factors Predicting Actual Usage of BCHI

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.226	.053		23.090	.000
	Age	.001	.001	.045	.713	.477
	Gender	-.048	.022	-.133	-2.159	.032
	Basic level of education	.126	.056	.140	2.259	.025
	Certificate/Diploma level of education	.107	.024	.295	4.488	.000
	Masters level of education	.112	.039	.184	2.885	.004
	PhD level of education	.212	.077	.169	2.740	.007

a. Dependent Variable: **Actual Usage of BCHI**

The regression analysis of demographic predictors on the log-transformed Actual Usage of Biometric Controlled Health Informatics (BCHI) as shown in Table 3 above reveals a distinct pattern of significant influences. Mirroring the findings for attitude, gender remains a significant predictor (β = -.133, p = .032), with male health workers reporting significantly lower levels of actual usage compared to their female counterparts. Educational level demonstrates even more pronounced and widespread significance in predicting usage behavior. Using a bachelor's degree as the reference category, health workers at nearly every other educational level reported significantly higher log-transformed usage scores. This includes those with a basic education (β = .140, p = .025), a certificate/diploma (β = .295, p < .001), a master's degree (β = .184, p = .004), and notably, those with a PhD (β = .169, p = .007). The strong, positive coefficient for the Certificate/Diploma group suggests they are the most active users relative to bachelor's degree holders. Consistent with the attitude model, age was not a statistically significant

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predictor of actual usage (β = .045, p = .477). These results indicate that while gender and educational background are robust demographic determinants of both attitude and practical engagement with BCHI, educational attainment exhibits a particularly strong and consistent relationship with the level of actual system use.

Table 4. Regression Analysis of Demographic Factors Predicting Perceived Usefulness towards BCHI

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.221	.054		22.798	.000
	Age	.002	.001	.098	1.551	.122
	Gender	-.058	.022	-.163	-2.616	.009
	Basic level of education	.061	.056	.068	1.078	.282
	Certificate/Diploma level of education	.101	.024	.279	4.202	.000
	Masters level of education	.044	.039	.073	1.139	.256
	PhD level of education	-.132	.078	-.105	-1.686	.093

a. Dependent Variable: **Perceived Usefulness of** BCHI

The regression analysis examining the demographic predictors of perceived usefulness as shown in Table 4 above reveals a more selective pattern of influence compared to attitude and actual usage. Gender again emerges as a significant predictor (β = -.163, p = .009), with male health workers perceiving the biometric system as significantly less useful than female workers when controlling for other variables. Regarding educational level, only one group showed a statistically significant difference from the bachelor's degree reference category. Health workers holding a certificate/diploma reported a significantly higher perception of the system's usefulness (β = .279, p < .001). In contrast, those with a basic education (β = .068, p = .282), a master's degree (β = .073, p = .256), and a PhD (β = -.105, p = .093) did not differ significantly from bachelor's holders in their perceived usefulness scores, though the negative coefficient for PhD holders approaches significance and suggests a trend toward lower perceived usefulness. Age remained a non-significant predictor in this model (β = .098, p = .122). These findings suggest that while gender influences perceptions across dimensions, the belief that the technology enhances job performance (perceived usefulness) is most strongly and uniquely associated with health workers who have mid-level vocational training (certificate/diploma), rather than those with higher academic degrees.

Table 5. Regression Analysis of Demographic Factors Predicting Perceived Easiness of BCHI

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.330	.047		28.543	.000
	Age	.000	.001	-.016	-.245	.806
	Gender	-.063	.019	-.204	-3.255	.001
	Basic level of education	.115	.049	.149	2.356	.019
	Certificate/Diploma level of education	.046	.021	.145	2.180	.030
	Masters level of education	.075	.034	.143	2.219	.027
	PhD level of education	.157	.068	.144	2.306	.022

a. Dependent Variable: **Perceived Easiness of BCHI**

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The regression analysis for Perceived Ease of Use as shown in Table 5 above presents the most consistent and widespread demographic influence observed across all TAM constructs. Gender maintained a strong and significant negative relationship (β = -.204, p = .001), indicating that male health workers find the biometric system significantly less easy to use than their female colleagues. Notably, in contrast to other models, every educational level demonstrated a significant positive effect on perceived ease of use when compared to the Bachelor's degree reference group. Health workers with a Basic education (β = .149, p = .019), a Certificate/Diploma (β = .145, p = .030), a Master's degree (β = .143, p = .027), and a PhD (β = .144, p = .022) all reported finding the system easier to use than those holding a Bachelor's degree. The standardized coefficients (Beta) are remarkably similar across these groups, suggesting a uniform educational advantage over the reference category. As with all previous models, age was not a significant predictor (β = -.016, p = .806).

Table 6. Regression Analysis of Demographic Factors Predicting Behaviour intention towards BCHI

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.232	.057		21.648	.000
	Age	.001	.001	.061	.946	.345
	Gender	-.036	.024	-.098	-1.539	.125
	Basic level of education	.100	.060	.107	1.665	.097
	Certificate/Diploma level of education	.077	.026	.203	2.997	.003
	Masters level of education	.118	.042	.187	2.851	.005
	PhD level of education	.145	.083	.111	1.743	.083

a. Dependent Variable: **Behaviour intention towards BCHI**

The regression analysis for behavioural intention as shown in Table 6 above reveals a pattern distinct from the other Technology Acceptance Model (TAM) constructs. Unlike the consistent findings for attitude, actual usage, perceived usefulness, and perceived ease of use, gender was not a statistically significant predictor of intention to use the biometric system in the future (β = -.098, p = .125). This suggests that while gender influences current attitudes, perceptions, and usage, it does not directly predict the future intention to adopt the technology when other demographic factors are controlled. For educational level, the findings show partial significance. Health workers with a Certificate/Diploma (β = .203, p = .003) and those with a Master's degree (β = .187, p = .005) reported significantly stronger behavioral intentions than those with a Bachelor's degree. The coefficients for those with a basic education (β = .107, p = .097) and a PhD (β = .111, p = .083) were positive and approached but did not reach conventional statistical significance. As with all other models, Age was not a significant predictor (β = .061, p = .345). These results indicate that future adoption intentions are most strongly shaped by specific mid-to-high levels of formal education (certificate/diploma and master's), while the influence of gender dissipates at this forward-looking stage of the acceptance process.

4 Discussion

The findings reveal that gender and educational attainment significantly predict BCHI acceptance among health workers, while age shows no effect. Notably, male participants reported less favorable attitudes, lower perceived usefulness and ease of use, and reduced actual usage compared to females—a pattern contrasting general technology adoption literature but rooted in healthcare-specific dynamics.

Male health workers voiced strong concerns about perceived surveillance and loss of autonomy, describing BCHI as "being watched" or "micromanaged," viewing it primarily as a tool to monitor presence rather than support clinical work. This ties into a threat to professional authority, where several male clinicians felt mandatory biometric checks contradicted their seniority and experience, framing the system

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as infantilizing. Adding to this, men often expressed skepticism about benefits, questioning how BCHI truly improved patient care and seeing it mainly as an administrative burden. These perceptions may explain the gender gap, aligning with biometric privacy research where men show higher skepticism , though the disparity vanishes when predicting future behavioral intention—indicating initial resistance doesn't derail long-term commitment.

Educational attainment emerged as the most nuanced predictor, defying a simple linear link to acceptance. Certificate/diploma holders—the core clinical and administrative workforce—demonstrated the highest levels across perceived usefulness, ease of use, and usage. Bachelor's degree holders (the largest group) lagged, especially in ease of use, where all others rated the system higher. This suggests vocational training better equips users for task-oriented tools like BCHI, while bachelor's-linked factors (e.g., workflows, expectations) create barriers. These results extend prior work on professional background in health IT, challenge biases favoring "highly educated" staff, and support non-significant age effects in professional contexts .

Integrating Alomari and Soh's UTAUT-HS model[53] for mIoT in Saudi hospitals reinforces these insights: Performance Expectancy and Social Influence drive intent, with Computer/English Self-Efficacy (CESE) as a strong predictor [53]. Their moderators highlight demographic variations, including Perceived Threat to Autonomy (PTA) for clinicians vs. non-clinicians and older users [53]. This synthesizes with Kitsiou et al. on demographics, Sultana and Akter [55] on psychological readiness, and James et al. [56] on biometric privacy/invasiveness.

Thus, BCHI implementation demands a holistic framework addressing this interplay. Strategies should tailor to demographics (e.g., clinicians, males, diploma holders), build self-efficacy, harness social influence, and design systems minimizing surveillance/autonomy threats—transparently balancing security, privacy, and invasiveness.

5 Conclusion

The research demonstrated that personality traits, demographics (such as age, education, and experience), and TAM factors (perceived usefulness and ease of use) together accounted for 52% of the variance in attitudes toward BCHI. Supporting qualitative evidence highlighted organizational factors like training in mitigating resistance.

These results connect directly to the study's aims and research questions, backed by robust empirical data (statistics, participant quotes, and models), underscoring BCHI's promise for improving accountability and efficiency in resource-constrained environments through complementary training and change management. A mixed-methods approach enhanced validity by combining quantitative results (e.g., surveys of 244 health workers indicating 57% familiarity with biometrics and SEM analyses accounting for 45-52% variance in acceptance and attitudes). This triangulation provided comprehensive insights into BCHI adoption challenges in Ugandan hospitals.

Practically, the study recommends focused strategies, including training for non-technical personnel (limited to 57% attendance-tracking familiarity) and solutions for technical glitches. Implementing these could propel BCHI adoption in Gulu and Soroti hospitals, strengthening data security, attendance accountability, and operational efficiency in line with Uganda's e-health agenda for reliable public health services.

Furthermore, policymakers in Uganda, including the Ministry of Health, Public Service Commission, district administrations, and ICT Authority, should draw on these insights to initiate staged BCHI pilots incorporating uniform standards, role-specific training, infrastructure improvements, and stringent privacy safeguards—advancing a user-centric digital health evolution.

Finally, future research should integrate advanced methodologies, widen geographic coverage, and probe additional variables to counter this study's shortcomings, notably its restriction to two regional referral hospitals, heavy reliance on qualitative methods, and limited depth in assessing personality effects, infrastructure issues, and enduring results.

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