Healthcare Workers' Awareness Level on Biometric Controlled Health Informatics: A Case of Uganda Public Hospitals

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Abstract: The successful implementation of Biometric Controlled Health Informatics is based upon end-user awareness and acceptance (World Health Organization, 2021). In Uganda, the national e-health strategy advocated for the adoption of Biometric Controlled Health Informatics to enhance hospital service delivery and data security (Ministry of Health, 2016). However, the integration of Biometric Controlled Health Informatics, a system designed to securely manage patient records and health workers' data, remains limited. Establishing the level of health workers' awareness is a critical step, as a lack of awareness and understanding can lead to resistance, improper use, and ultimately, the failure of such technological interventions (Nigam et al., 2022 & Venkatesh & Bala, 2008This study established awareness of Biometric Controlled Health Informatics among clinical and non-clinical health workers at Gulu and Soroti Regional Referral Hospitals, offering valuable insights to guide tailored implementation strategies for this innovative technology in Uganda's health system. Using a mixed methods approach that combined qualitative and quantitative techniques within one study (Creswell & Plano Clark, 2023), the research provided a comprehensive understanding of the issue. The quantitative phase examined the relationship between health workers' personality traits (independent variables) and their acceptance of biometric-controlled health informatics (dependent variable) through standardized tools: the Big Five Inventory (BFI) and a Technology Acceptance Model (TAM) questionnaire. This enabled statistical analysis using correlation and multiple regression to measure the strength and direction of these relationships (Pallant, 2020).

The sample included 244 health workers from Gulu (52.0%) and Soroti (48.0%) hospitals, with this balanced representation reducing potential institutional bias. Quantitative results showed that around 57% of participants had prior knowledge of biometric authentication systems, and about 56.6% had used biometric data—primarily fingerprint scanning for attendance monitoring. Qualitative findings revealed that while most non-technical staff recognized biometrics mainly as attendance tools, technical staff were more aware of their broader use in securing patient records. However, there was limited understanding of biometric applications beyond attendance, highlighting a need for enhanced training and awareness programs.

Challenges such as technical glitches and perceptions of biometrics as controlling rather than enabling technology influenced levels of awareness and acceptance among health workers.

Keyword: *Biometric, Health Informatics, TAM, Philosophy, Acceptance, Public Hospitals, Uganda.*

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I. INTRODUCTION

Health informatics (HI) refers to the structured use of Information and Communication Technology (ICT) in public health, research, and education (Yogesh & Karthikeyan, 2022; Magnuson & Dixon, 2020; William et al., 2009). It involves the implementation, development, maintenance, design, surveillance, information systems, and evaluation of communication within the health sector. Health informatics improves processes such as scheduling appointments, conducting tests, and prescribing treatments (Addo & Agyepong, 2024; Andre, 2012). It also supports the generation,

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storage, and use of medical knowledge (Turban et al., 2007). The system offers many benefits, including access to clinical and administrative data (diagnoses, prescriptions, test results), recording patient interactions, managing appointments, and generating invoices.

Despite its advantages, the adoption of health informatics faces challenges like limited information availability and quality, poor integration of health information systems, medical errors, inadequate communication infrastructure, partial availability of data, fragmented and costly health information systems, and health workers' reluctance to adopt Hospital Information Systems (HIS) (Andre, 2012; Mantzana et al., 2008). Uganda has introduced e-health strategies to accelerate health informatics adoption and improve service delivery (MOH, 2016).

Biometric systems use unique human traits for identification (Stephen, 2004). These traits are categorized into genotypic (DNA patterns, hand and facial geometry), randotypical (fingerprints, iris, hand veins), and behavioral (typing patterns, signature dynamics). Biometrics enable reliable identification of health workers based on these characteristics. Due to weaknesses in password security—such as employees sharing passwords with colleagues or writing them down—biometric authentication is gaining popularity in healthcare (Mogli, 2011). Passwords, PINs, and smart cards can be easily compromised, risking patient privacy and medical record security.

Biometrics is widely used in many fields, including smartphone unlocking and airport security (Mason et al., 2020). It provides secure and convenient individual identification. However, the slow adoption of biometric health informatics systems among healthcare professionals is linked to factors like low intention to use, limited user involvement, and inadequate preparation (Hamapa et al., 2024; JunHua et al., 2008; Aditya et al., 2011).

Another key issue is neglecting health workers' personality traits during system design. Since personality shapes individuals' thoughts and behaviors (Edward et al., 2019), a mismatch can hamper adoption. Personality, defined as a stable set of traits influencing emotions and behaviors, affects technology acceptance (Wilburn & Chris, 2012). Men (53%) are more likely than women (47%) to own smartphones. This study focuses on the Big Five personality traits—agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience—and explores their influence on health workers' acceptance of biometric-controlled health informatics in two public hospitals (Wilburn & Chris, 2012; Tan et al., 2012).

II. LITERATURE REVIEW

➢ *Theoretical Framework*

According to Vogt (2005), a theory is a collection of assertions or a statement that describes the workings of the world as it is, as well it typically explains relationships between events. The foundation of analysis is a theory, which also helps the area develop creatively and is essential for applying to practical issues (Gelso, 2006). Researchers have made attempts to elucidate their theories using typologies, but there is a little consensus on the meanings of these terms (Gelso, 2006; Gay & Weaver, 2011; Creswell, 2009; Heinen, 1985; Harlow, 2009; Kerlinger, 1986; Stam, 2010a, 2010b; Staw & Sutton, 1995; Whetten, 1989; Wacker, 1999).

It is said that researching information technology for the medical field is like aiming for a moving target. Social ideas that were in place before to its ascent must be replaced with new ones. As a result, reality must be simplified, but this should not be done to the point where the subtleties that define this complexity are obscured (Kathrin et al., 2010).

Due to extensive systematic literature search and review of relevant theoritical framework test books and peer reviewed journals this study would make use of Technology Acceptance Model (TAM) to underpin this study

➢ *Technology Acceptance Model (TAM).*

Technology Acceptance Model as presented in (Fig. 1) is a significant theoretical contribution towards understanding acceptable IT behaviour and usage, according to Yogesh & Dennis (1999). Manon (2008) asserts that the only significant indicator of usage intention appears to be perceived usefulness. The intention to utilize virtual reality is not directly influenced by basic factors like attitude, perceived cost, or perceived ease of use. Nonetheless, a number of information systems experts have pointed out that the Technology Acceptance Model is deficient since it ignores the role that society plays in the acceptance of new information systems. Davis (1986) and Davis et al. (1989) argue that the construct that represents social impact, the subjective norm (SN), must be taken into account. They found that, as the following figure illustrates, it might be challenging to determine whether usage habits are a result of impact on a person's attitude or objective.

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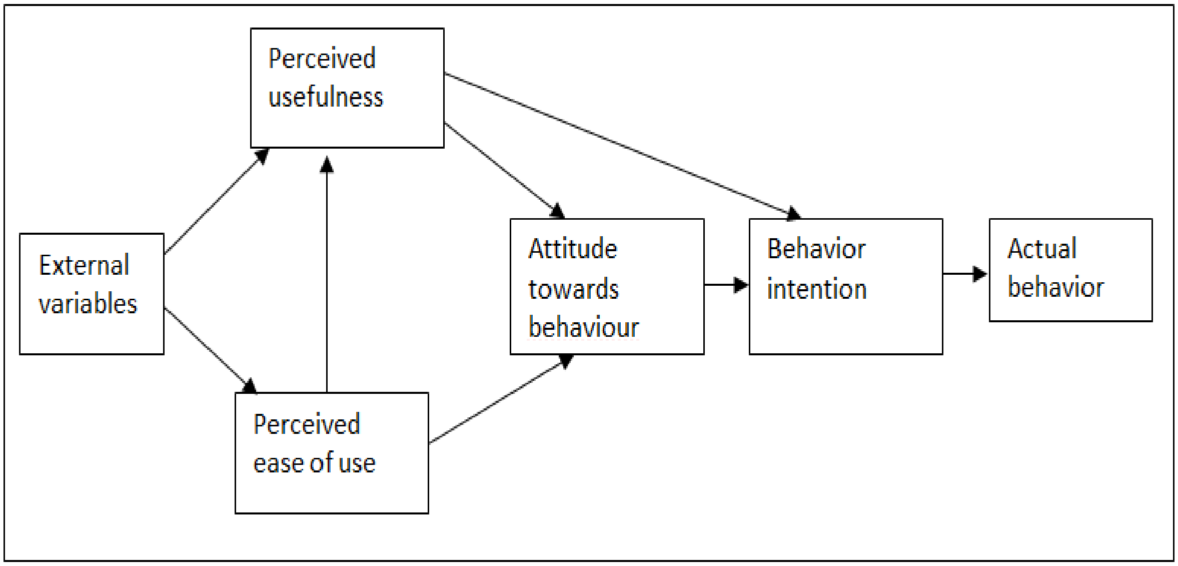

Fig 1: Technology Acceptance Model (Davis et al., 1989)

A variety of arguments have been put out to explain why adoption of technology is so delayed in hospitals. Currently being addressed include barriers related to insufficient research, inadequate legal framework or models, lack of standardization, and financial and technological restrictions (Chen 2020, Amatayakul, 2004; Thompson & Brailer, 2004). Yet human factor-related challenges, like, user behaviour and acceptance, still exist (Chen 2020). Moreover, user behavior has been implicated in several healthcare system implementation failures (Chen 2020)

The implementation of Information Technology (IT) in healthcare organizations was proven by a rigorous analysis of health informatics. However, a study by Bahlol et al (2018), posits that lack of models to assess user personality traits in figuring out whether or not Health Informatics would be accepted is a challenge that still needs further investigations.

III. MATERIALS AND METHOD

➢ *Participants and Procedures*

Health workers from Gulu and Soroti Regional Referral Hospitals in Uganda were selected using simple random sampling. A total of 400 paper questionnaires were distributed evenly between the two districts, with participants completing them during face-to-face sessions assisted by enumerators. The study emphasized that the data collected was solely for research, encouraging honest and anonymous responses.

After removing incomplete and invalid questionnaires, the final sample included 244 health workers, with 52.0% from Gulu and 48.0% from Soroti. Females slightly outnumbered males, representing 52.0% of respondents. The largest age group was 41-60 years (40.2%), followed by 31-40 years (34.4%) and 19-30 years (25.4%). This suggests the sample mainly consisted of experienced, middle-aged, and older professionals.

Age may influence technology adoption, as older workers often show reluctance to new systems due to technophobia and a preference for traditional methods, while younger staff tend to embrace digital innovations more readily. Personality traits also play a role; for example, perfectionist tendencies may necessitate extra quality assurance during biometric system implementation, and individuals low in agreeableness may exhibit resistance (John & Srivastava, 1999).

IV. METHODOLOGY

This study adopted a sequential mixed-methods approach, beginning with the collection and analysis of quantitative data, followed by qualitative data collection and analysis. This design is well-suited for using qualitative insights to enhance, explain, and build upon the quantitative findings (Shorten & Smith, 2017). The priority of the quantitative approach is established by its role in addressing the core objective of measuring the prevalence and strength of relationships between variables across a representative sample. Specifically, the quantitative study provides the primary data to objectively assess the level of awareness of BCHI systems. This dominant quantitative component ensures the findings are grounded in empirical, generalizable evidence, forming the central narrative of the study.

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V. EVALUATION OF CURRENT HEALTH RECORD SYSTEMS

Category	Frequency	Percentage
Paper-based health record	60	24.6%
Health Information system	184	75.4%
Total	**244**	**100.0%**

Source; primary data, 2025

The findings reveal a critical distinction between system availability and functional application. While 75.4% of healthcare workers report using a Health Information System (HIS), qualitative findings show that this usage is predominantly confined to attendance monitoring rather than patient data management. This represents a significant implementation gap where digital infrastructure is being underutilized for its primary purpose of enhancing healthcare delivery (Katuuhu et al., 2023). The high adoption rate is therefore misleading without contextual understanding - it indicates system accessibility but not necessarily integration into clinical workflows or patient care processes. This limited functional application suggests what Muhaise, et al (2019) noted that technology is used minimally to satisfy administrative requirements without transforming core healthcare practices. The persistence of paper-based records among 24.6% of staff, coupled with the narrow usage pattern of digital systems, show fundamental barriers to meaningful digital transformation. When Biometric-Controlled Health Informatics are primarily utilized for attendance tracking, it indicates mistrust in digital record-keeping, and workflow designs that make paper systems more practical for patient care. This creates a dual challenge for biometric system implementation: not only must the technology be introduced, but healthcare workers must also be guided toward recognizing its value beyond basic administrative functions. The current pattern suggests that without addressing these underlying issues, biometric systems risk following the same path of limited utilization, becoming merely sophisticated time clocks rather than transformative tools for securing patient data and enhancing clinical care.

VI. HEALTH WORKERS' AWARENESS OF BIOMETRIC-CONTROLLED HEALTH INFORMATICS

The critical realism philosophy was instrumental in structuring the findings on health workers' awareness of Biometric Controlled Health Informatics (Kempton, 2022; Zhang, 2023). Critical realism provided a stratified framework that distinguished between the what health workers reported and were observed doing, the events and patterns of technology use that occurred, and the underlying social and institutional structures shaping awareness. (Collier, 1994; Kempton, 2022). Critical realism philosophy compelled the research to move beyond a description of "what" health workers knew. It directed the research to initially record the discernible levels of awareness and subsequently elucidate the rationale behind the specific structuring of that awareness (Zhang, 2023). This approach guided the study by recording what health workers said they knew, and also having an explanation of why their understanding was structured in that particular way. The initial empirical study quantified a high level of basic awareness, with most 75.4% respondents identifying the biometric system's primary function for staff attendance tracking. However, the subsequent interviews and focus group discussions revealed this awareness was superficial. A typical expression was by the administrator at Soroti Hospital, who stated, "I have no idea how it works. We just press our fingers and it records," which shows a widespread operational knowledge without deeper understanding of Biometric Controlled Health Informatics in public hospitals in terms of protection of patients' data. The analysis revealed that the limited understanding of underlying mechanisms in the real domain of critical realism was not accidental. Instead, it was fundamentally shaped by a deficit of trust in the hospital, where the staff questioned management's motives for implementing a system they perceived as primarily for surveillance. This perception created widespread technological anxiety and reinforced workplace power dynamics that actively discouraged health workers from seeking further information about the system's operations. This philosophical framework was therefore crucial for moving from the surface-level finding of high awareness to the more meaningful explanation of a fragile and narrow understanding rooted in the hospital's socio-technical environment.

The sequential mixed-methods approach was critical to achieving an understanding of health workers' awareness, as neither quantitative nor qualitative methods alone could fully unravel the whole reality (Creswell & Plano Clark, 2018). The quantitative phase established the "what": it provided broad, generalisable data regarding health workers' awareness of Biometric Controlled Health Informatics in public hospitals, revealing that 75.4% of health workers used biometric technology, but their interaction was almost exclusively confined to a single function, namely, recording attendance. This phase successfully documented the widespread, yet functionally narrow, usage pattern across Gulu and Soroti Regional Referral Hospitals. However, as DeVellis (2017) notes, surveys are excellent for identifying patterns but often fall short of explaining the social and cognitive processes behind them. The survey data, for instance, could not explain why this "compliance without comprehension" existed regarding other functional aspects of Biometric Controlled Health Informatics, such as data privacy and broader system

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capabilities in these public hospitals. Through interviews and focus group discussions, the research uncovered the experiences and perceptions of the health workers' awareness of Biometric Controlled Health Informatics in these public hospitals. The narrative data revealed that for many health workers, the biometric system was not an integrated health informatics tool but a simple electronic time clock. This is powerfully encapsulated in the statement from an accountant at Gulu Hospital: "Basically here, what we know is just when you're signing in. You just come and sign in, and when you're moving out, you sign up. That is all I know about biometrics." This finding, representative of a common sentiment, explains the quantitative data by showing that high usage rates did not equate to a deep, functional awareness of BCHI's potential. This integration of data types is what Fetters, Curry, and Creswell (2013) describe as the core strength of mixed methods, where one form of evidence elucidates the other.

The sequential design helped in investigating and explaining the findings. The initial quantitative analysis identified a statistical anomaly: there was no significant correlation between a health worker's education level and their awareness of biometric technology ($r = 0.12$, $p > 0.05$). A purely quantitative study would have been forced to leave this finding as an unexplained inconsistency. However, by following a sequential model, the research used the qualitative phase to deliberately probe this unexpected result (Ivankova, Creswell, & Stick, 2006). The interviews uncovered that resistance or acceptance was less about cognitive capacity and more about institutional culture and mindset. As one respondent indicated, "Not everyone appreciates change, so the mindset was kind of negative at the start," showing how psychosocial and organisational factors could override individual educational attainment. The study's findings show a clear alignment with the integrated deductive-retroductive reasoning strategy, serving to test established theories. The deductive reasoning process was validated through the quantitative findings that confirmed several hypothesized relationships derived from the Technology Acceptance Model (TAM) and the Big Five personality framework. For instance, the significant positive correlation between Openness to Experience and Perceived Usefulness ($r = .342$, $p < .001$) empirically supported the theoretical proposition that individuals with a greater appetite for novelty would be more likely to recognise the utility of a new technology (Davis, 1989; John & Srivastava, 1999). Similarly, the correlation between Conscientiousness and Perceived Ease of Use ($r = .267$, $p < .001$) affirmed the deductive hypothesis that orderly, disciplined individuals would find structured technological systems more intuitive. These results demonstrate a classic deductive cycle: from general theory (TAM, Big Five) to specific hypotheses, and finally to empirical confirmation through survey data, thereby strengthening the external validity of these established models within the Ugandan public health system (Saunders, Lewis, & Thornhill, 2019).

The retroductive reasoning process was powerfully illustrated by the investigation into the underlying causes of the compliance without comprehension of the system. As Mingers (2004) advocates, retroduction involves theorising the unobservable structures that generate observable events. The quantitative data provided the initial puzzle: high usage rates (75.4% for attendance) coexisted with shallow understanding. The retroductive process then asked, as Sayer (2000) formulates, "What must be true for this phenomenon to exist?" The qualitative findings revealed the underlying social and institutional structures, such as workplace power dynamics that discouraged inquiry and a deficit of institutional trust, created an environment where surface-level compliance was the path of least resistance. This was not a relationship that could be deduced from existing theory alone; it required an abductive leap to identify these latent, causal mechanisms. The finding that education level did not correlate with awareness ($r = 0.12$, $p > 0.05$) further necessitated retroductive explanation, leading to the discovery that technological self-efficacy and institutional trust were more powerful determinants than formal education, a nuanced insight that extends existing theory. The deduction provided the necessary framework to identify what was happening in a generalisable way, while retroduction unlocked the deeper understanding of why it was happening in this specific context. For example, deduction confirmed that personality traits influence acceptance, but it was retroduction that uncovered how these traits interacted with the unique socio-technical environment of a Ugandan public hospital, such as a neurotic individual's anxiety being amplified by unreliable systems and an agreeable person's trust being eroded by opaque management motives. This allowed the study to provide a more contextually grounded explanation that accounts for the hospital realities and power structures shaping technology acceptance in healthcare (Wynn & Williams, 2012).

VII. CONCLUSION

This research examined the awareness, acceptance, and attitudinal foundations of Biometric-Controlled Health Informatics in two Ugandan national referral hospitals. The findings illuminate a nuanced picture: biometric systems are present and moderately known among staff, but knowledge is often restricted to attendance systems rather than broader informatics functionality; personality traits (notably conscientiousness and openness) and TAM-related perceptions (usefulness, ease of use) jointly and substantially shape acceptance and attitude; and organizational supports (training, transparent leadership, reliable technology) can modify or amplify dispositional tendencies.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Unicaf University REC, Uganda National REC, The Uganda National Council for Science and Technology (UNCST), and administrative clearance from both regional referral hospitals, ensuring ethical standards were met.

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