Investigating Determinants of Health Information System Adoption in Tanzania's Public Healthcare: An Integrated Framework based on UTAUT, DeLone & McLean, and Diffusion of Innovations Theory

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ABSTRACT
The successful adoption of Health Information Systems is fundamental to improving efficiency, accountability, and decision-making in public healthcare, particularly in low and middle income countries. This study investigates the determinants influencing the implementation of the Government of Tanzania Hospital Management Information System. Drawing on an integrated theoretical framework comprising the Unified Theory of Acceptance and Use of Technology, the DeLone and McLean IS Success Model, and the Diffusion of Innovations theory a cross sectional survey was conducted involving 406 healthcare professionals from four public hospitals in Tanzania. Using Exploratory Factor Analysis and Structural Equation Modeling, the study validated 7 out of 13 hypothesized relationships. Information quality, service quality, system use, communication, compatibility, behavioral intention, and trialability emerged as significant predictors of system implementation. In contrast, constructs such as effort expectancy, user satisfaction, and facilitating conditions showed no statistical significance. The study concludes that institutional and infrastructural enablers outweigh individual perceptions in influencing HIS adoption. Recommendations include enhanced investment in ICT infrastructure, structured pilot testing, continuous user training, and policy reinforcement to support nationwide Health Information Systems integration in public healthcare delivery.

General Terms
Health Information Systems, Technology Adoption, Public Healthcare.

Keywords
GOTHOMIS, Health Information System, UTAUT, DeLone and McLean, SEM, Tanzania, ICT in healthcare.

1. INTRODUCTION
In the contemporary landscape of global health reform, digital innovations have become indispensable for advancing healthcare efficiency, equity, and sustainability. Increasingly, countries are deploying Health Information Systems (HIS) to improve data accuracy, streamline clinical coordination, and strengthen the responsiveness of health policies. For instance, [1] underscores the critical role of HIS as foundational infrastructure for achieving universal health coverage, enabling both policy formulation and performance monitoring in resource-constrained health systems. Similarly, [2] found that health professionals demonstrate greater responsiveness to care demands when supported by robust information systems.

The historical gap between high-income and low-income countries in HIS implementation is progressively narrowing, as digital health tools gain momentum across Sub-Saharan Africa. [3] notes that HIS in African countries are increasingly leveraged to address chronic operational inefficiencies within public health facilities. These technologies are no longer perceived as optional enhancements but as strategic imperatives for effective service delivery. Indeed, [4] asserts that HIS can furnish decision-makers with data-driven insights, particularly in contexts where manual systems have proved inadequate. This growing urgency has prompted many governments to prioritize e-health initiatives in their national development agendas.

In Tanzania, the Government of Tanzania Hospital Management Information System (GOTHOMIS) was introduced to standardize hospital operations and facilitate integrated patient care. This initiative aligns with the broader national digital transformation agenda championed by Her Excellency President Samia Suluhu Hassan, whose administration has prioritized the modernization of public service delivery through technology. According to [5], GOTHOMIS was designed to address persistent challenges such as fragmented patient records and delays in data retrieval. Its deployment enables real-time analytics, which are critical for health workforce planning and medical supply chain management. Recent evidence from [6] indicates that more than 60% of Primary Health Care facilities now employ GOTHOMIS for routine health data collection. Furthermore, [7] highlights the system's alignment with national digital health strategies advocating the institutionalization of e-governance.

Despite its conceptual robustness, GOTHOMIS implementation remains inconsistent across Tanzanian health facilities, posing challenges for policy and practice. While [8] observes tangible improvements in recordkeeping within some hospitals, others continue to grapple with infrastructural limitations. These disparities have been linked not only to technical challenges but also to socio-organizational and behavioral factors, including staff resistance and insufficient change management [9]. Indeed, [10] argues that technological readiness alone does not guarantee adoption; rather, successful implementation requires contextual adaptation, institutional commitment, and sustained support.

To better understand and guide effective adoption, several theoretical models offer valuable insights into the behavioral and systemic drivers of HIS utilization. The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by

[11] emphasizes user perceptions of system usefulness and effort expectancy, both of which strongly influence engagement among frontline health workers. Complementing this, the Diffusion of Innovations Theory advanced by [12] stresses the significance of compatibility and observability in technology adoption. Additionally, [13] identifies system quality, user satisfaction, and service support as critical dimensions of HIS success.

However, there remains a notable empirical gap regarding how these models operate within the Tanzanian public healthcare context. Studies by [14] and [3] suggest that many existing frameworks are derived from high-income settings and require adaptation to local realities. Moreover, [15] reports that socio-technical infrastructure, policy design, and institutional culture significantly shape adoption outcomes in low- and middle-income countries. This study seeks to address this gap by examining the technological, individual, and organizational factors influencing GOTHOMIS adoption. The findings will contribute to the evolving body of literature on digital health and inform policy frameworks that foster effective HIS utilization in Tanzania.

2. LITERATURE REVIEW

This section provides a comprehensive review of the theoretical and empirical literature underpinning the adoption of HIS, with a particular focus on the Government of GOTHOMIS. The review is divided into two main parts. The first Section presents the theoretical literature review, drawing on established models such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the DeLone and McLean Information Systems Success Model, and the Diffusion of Innovations (DOI) theory to formulate research hypotheses. The second section synthesizes empirical evidence from global, regional, and Tanzanian contexts to contextualize the study and identify prevailing gaps. The integration of theoretical constructs and empirical findings lays a robust foundation for the development of a multidimensional framework to assess GOTHOMIS adoption in Tanzania's public healthcare institutions.

2.1 Theoretical Framework

Understanding the dynamics that influence the implementation of digital health systems in public institutions requires more than a superficial application of adoption models. It demands a multidimensional theoretical approach that captures individual cognition, institutional infrastructure, and socio organizational structures. To that end, this study integrates three seminal theoretical perspectives UTAUT, the DeLone and McLean Information Systems Success Model, and Rogers' Diffusion of Innovations Theory to develop a robust framework for analyzing the determinants of GOTHOMIS implementation in Tanzania's public healthcare system.

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by [16] is particularly effective for examining individual acceptance behavior within institutional settings. This model is grounded in the empirical synthesis of eight prominent adoption theories, and it identifies four important determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. In clinical environments, performance expectancy is arguably the most powerful driver, as users must perceive that the system will directly enhance their capacity to deliver patient care. The literature affirms that this belief significantly influences the willingness of healthcare professionals to embrace hospital information systems [17]; [6]. Thus, it is theoretically sound to propose that performance expectancy positively affects GOTHOMIS implementation.

Effort expectancy, the second UTAUT construct, underscores the principle of cognitive economy. If the system appears difficult to learn or operate, especially among staff with limited exposure to digital systems, resistance is inevitable. Numerous studies have established that perceived ease of use is an antecedent to sustained interaction with HIS [18]. [7] further posits that simple interface design and minimal data entry complexity improve adoption outcomes. Therefore, effort expectancy is hypothesized to positively influence the implementation of GOTHOMIS.

The role of social structures particularly in hierarchical and collectivist cultures cannot be overstated. Social influence, as conceptualized in UTAUT, pertains to the normative pressure exerted by colleagues, supervisors, and institutional leadership. [19] emphasize that managerial endorsement and peer reinforcement significantly shape technology adoption patterns in healthcare settings. Given the bureaucratic nature of Tanzanian public institutions, social influence is expected to play a pivotal role in determining GOTHOMIS implementation.

The fourth UTAUT pillar, facilitating conditions, links intention to actual behavior through the availability of institutional support mechanisms. [20] argue that no matter how positive a user's disposition is, adoption cannot be sustained without reliable access to internet connectivity, hardware, and ongoing training. [18] echoes this sentiment, highlighting how infrastructural deficiencies often derail e health initiatives in Sub Saharan Africa. Accordingly, facilitating conditions are hypothesized to positively impact the behavioral intention to implement GOTHOMIS.

Moreover, both behavioral intention and user attitude emerge as significant mediators in technology acceptance. While behavioral intention captures an individual's readiness to adopt a system, it is highly sensitive to enabling conditions and perceptions of efficacy [5] and [21] Attitude, on the other hand, reflects deeper emotional orientations that evolve through experience and reflection. [22] argue that early user experiences positive or negative leave lasting impressions that shape the trajectory of system usage. In light of this, it is posited that both behavioral intention and user attitude positively influence the implementation of GOTHOMIS.

To complement the pre adoption lens of UTAUT, this study incorporates the DeLone and McLean Information Systems Success Model 0f 2003, which focuses on post adoption outcomes. In this model, system use and user satisfaction are both outcomes and predictors of success. Information quality, a central construct, is especially vital in healthcare environments where clinical decisions depend on accurate, timely, and relevant data. When information integrity is compromised, user trust deteriorates and system use declines [10]. Thus, information quality is expected to significantly enhance the implementation of GOTHOMIS.

System quality refers to the technical performance of the platform its reliability, speed, and security. In contexts where system crashes and latency are common, user frustration rises, leading to withdrawal from system usage. A Study by [23] confirm that users are more inclined to engage with systems that are stable, intuitive, and fast. Therefore, system quality is theorized to have a positive effect on GOTHOMIS implementation.

Service quality captures the support infrastructure surrounding system use, such as user training, troubleshooting, and

technical responsiveness. As observed by [4], even technically robust systems may be rejected if users lack access to timely and empathetic support. Service quality thus serves as a mediator between system functionality and user satisfaction, and it is proposed to have a direct positive influence on the latter.

User satisfaction itself is a cumulative measure of perceived usefulness, ease of use, system stability, and service responsiveness. It plays a key role in sustaining behavioral intention and ensuring long term system engagement. [10] assert that satisfied users are more likely to advocate for continued investment in digital systems and engage in meaningful system use. Therefore, satisfaction is hypothesized to influence GOTHOMIS implementation positively.

System use is not merely an outcome; it is also a proxy for system integration and institutional normalization [24] argue that consistent system use correlates with improved organizational outcomes. In the context of this study, increased frequency and depth of interaction with GOTHOMIS is expected to signal greater institutional alignment. Accordingly, system use is proposed to positively influence implementation success.

To enrich this analysis with a socio organizational perspective, this study also draws on Rogers' Diffusion of Innovations (DOI) Theory of 2003. DOI highlights the importance of innovation attributes such as communication, compatibility, and trialability in shaping adoption decisions. Communication is essential for managing uncertainty, aligning expectations, and promoting shared understanding. [20] and [16] show that poor communication leads to fragmented implementation, while consistent messaging fosters institutional buy in. Therefore, communication is hypothesized to positively affect GOTHOMIS implementation.

Compatibility is another important DOI attribute, reflecting the degree to which the innovation aligns with user values, existing workflows, and organizational norms. [25] caution that misalignment between digital systems and existing practices often leads to resistance and passive disengagement. Thus, it is expected that compatibility enhances GOTHOMIS implementation.

Trialability the extent to which users can experiment with the system prior to full scale deployment provides an avenue for feedback, learning, and adaptation. Pilot testing serves not only to validate system design but also to reduce user anxiety and build institutional confidence [15]. As such, trialability is theorized to positively impact the implementation of GOTHOMIS.

Finally, it is imperative to link system implementation to its ultimate purpose the improvement of healthcare delivery. As digital systems transform administrative and clinical processes, they should yield observable benefits such as reduced waiting times, enhanced accuracy of records, and improved policy planning. [10] and [26] contend that successful HIS implementation leads to measurable performance improvements, particularly in low resource settings. Therefore, the final hypothesis asserts that the implementation of GOTHOMIS positively influences healthcare service delivery.

In light of the theoretical perspectives discussed and the empirical insights drawn from previous studies, this research advances a series of hypotheses to empirically test the relationships among the identified constructs. These hypotheses are formulated to examine both individual level and organizational level factors influencing the implementation of GOTHOMIS in Tanzania's public healthcare system. The proposed hypotheses are as follows;

H1: Performance expectancy has a positive effect on the implementation of GOTHOMIS.

H2: Effort expectancy has a positive effect on the implementation of GOTHOMIS.

H3: Social influence has a positive effect on the implementation of GOTHOMIS.

H4: Facilitating conditions have a positive effect on behavioral intention to implement GOTHOMIS.

H5: Behavioral intention has a positive effect on the implementation of GOTHOMIS.

H6: User attitude has a positive effect on the implementation of GOTHOMIS.

H7: User satisfaction has a positive effect on the implementation of GOTHOMIS.

H8: System use has a positive influence on the implementation of GOTHOMIS.

H9: Information quality has a positive effect on the implementation of GOTHOMIS.

H10: System quality has a positive effect on the implementation of GOTHOMIS.

H11: Service quality has a positive effect on user satisfaction for GOTHOMIS implementation.

H12: Communication has a positive effect on the implementation of GOTHOMIS.

H13: Compatibility has a positive effect on the implementation of GOTHOMIS.

H14: Trialability has a positive effect on the implementation of GOTHOMIS.

H15: The implementation of GOTHOMIS has a positive influence on healthcare service delivery.

2.1.1 Conceptual framework

The conceptual framework guiding this study is developed by integrating three theoretical perspectives: the Unified Theory of Acceptance and Use of Technology (UTAUT), the DeLone and McLean Information Systems Success Model, and the Diffusion of Innovations (DOI) Theory. Each of these theories provides complementary insights into the behavioral, technical, and contextual factors influencing the implementation of GOTHOMIS in Tanzania's public healthcare sector. The resulting framework reflects a multi theoretical lens suitable for understanding complex information system adoption in low resource settings.

From the UTAUT perspective, the framework includes performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of behavioral intention and system use. These constructs capture users' expectations, social pressures, and institutional support systems, which together influence their willingness to engage with GOTHOMIS. Additionally, user attitude and behavioral intention are incorporated to reflect personal dispositions and motivational drivers toward system usage.

The DeLone and McLean IS Success Model introduces constructs such as system quality, service quality, information quality, user satisfaction, and system use. These factors are

important in assessing post implementation outcomes and ensuring that the system delivers value to users. Their inclusion in the framework acknowledges that both technical reliability and support services are pivotal for sustained adoption.

The DOI theory complements this by emphasizing innovation characteristics such as communication, compatibility, and trialability. Communication reflects the clarity and reach of implementation messages, compatibility refers to the fit between GOTHOMIS and existing clinical workflows, and trialability measures the ability to experiment with the system on a limited scale before full adoption. These attributes explain the speed and extent of GOTHOMIS diffusion across facilities.

Collectively, the framework hypothesizes that these constructs interact to influence the degree of GOTHOMIS implementation, which in turn affects the quality of healthcare service delivery. This conceptual alignment ensures that both user perceptions and system attributes are adequately addressed, offering a robust explanatory model for adoption behavior in the public health sector.

The conceptual model presented in Figure 1 illustrates the hypothesized relationships among the constructs derived from UTAUT, DeLone & McLean IS Success Model, and DOI theory. These constructs collectively inform the expected determinants of GOTHOMIS adoption in Tanzania's public healthcare context.

2.2 Adoption of Health Information Systems

The adoption of HIS has increasingly become a global health priority, driven by the need to improve service delivery, ensure data reliability, and enhance policy responsiveness. In high income countries, particularly in North America and Western Europe, HIS most notably Electronic Health Records (EHRs) have been widely adopted with significant benefits. According to [24], countries such as Finland, Norway, and the Netherlands report over 90% EHR penetration in public hospitals, with positive effects on patient safety, clinical documentation, and administrative efficiency. Similarly, [9] found that in the UK, EHR implementation led to improved care coordination and reduced medical errors, particularly when complemented by strong regulatory frameworks and continuous stakeholder engagement.

Nonetheless, despite these successes, barriers persist. [27] identified clinician burnout and dissatisfaction with system usability as major impediments to sustained adoption, while [28] highlighted interoperability issues and resistance to change as prevalent in both private and public healthcare settings. These findings underscore the continued relevance of technology adoption theories, especially the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of user intention and behavior [26]. Moreover, [4] noted that even when digital health systems are functional, marginalized groups often face access barriers due to inadequate digital literacy and lack of culturally tailored interfaces.

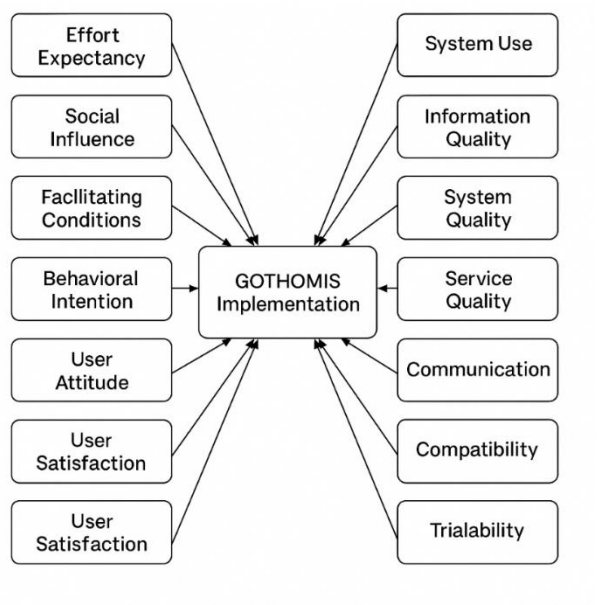

Figure 1: Integrated Conceptual Framework for GOTHOMIS Implementation Based on UTAUT, DeLone & McLean IS Success Model, and DOI Theory

In contrast, low and middle income countries, particularly those in Sub Saharan Africa, face additional structural and institutional constraints that further complicate HIS adoption. In Kenya, [29] reported that while the national rollout of HIS had begun in public hospitals, system underutilization was common due to unreliable power supply, poor internet connectivity, and insufficient change management strategies. These infrastructural challenges were compounded by limited system customization and the exclusion of end users from the design process. Similar findings were reported by [3] in Nigeria, where HIS projects often suffered from fragmented governance, policy misalignment, and poor integration with existing health data systems. These studies confirm that in resource constrained settings, beyond technological capabilities, the socio organizational environment significantly shapes adoption outcomes.

In Ethiopia, [2] conducted a national survey that identified performance expectancy, training support, and system reliability as the strongest predictors of electronic medical record acceptance among health professionals. Importantly, the study found that healthcare workers who received periodic refresher training and technical support were more likely to use digital systems consistently. This supports the claim by [30] that compatibility the degree to which a system fits within the user's workflow and institutional culture is a decisive factor in determining system uptake and long term usage. In Uganda, [31] further emphasized the role of leadership and top down mandates, showing that endorsement by institutional leaders significantly influenced frontline adoption, even when technical barriers existed.

In Ghana, a study by [32] on EMR compatibility revealed that systems misaligned with clinical processes resulted in increased documentation burden and reduced satisfaction among users. These findings reinforce [12] Diffusion of Innovation theory, which posits that innovation adoption is facilitated by high compatibility, observability, and trialability. Therefore, technological interventions in healthcare must be context sensitive and designed with a nuanced understanding of institutional routines and user behavior.

In the Tanzanian context, the (GOTHOMIS) was introduced as a cornerstone of the country's digital health transformation agenda. Despite its nationwide rollout, empirical studies suggest that GOTHOMIS remains underutilized in many public hospitals. [30] reported that only a fraction of district health managers regularly use GOTHOMIS data for planning and decision making. The study attributes this gap to poor data quality, lack of real time feedback, and minimal managerial training on data interpretation. These findings are consistent with [33], who emphasized the importance of facilitating conditions such as availability of technical support, internet stability, and administrative backing in influencing system engagement.

Additionally, participatory action research by [34] revealed that health workers often felt excluded from the system design and implementation process, resulting in low system ownership and reduced motivation to use GOTHOMIS. This lack of inclusivity contributed to a perceived misalignment between the system's functionality and users' daily routines. [35] similarly noted that several hospitals reported dissatisfaction due to the system's failure to reflect local documentation needs and workflow patterns, leading to resistance and passive usage. These findings mirror theoretical perspectives from both UTAUT and the DeLone and McLean IS Success Model, wherein performance expectancy and user satisfaction are significantly shaped by system quality and service delivery mechanisms.

Moreover, the literature indicates that communication breakdowns between system developers, implementers, and end users present a recurring bottleneck. [10] observed that poor feedback loops and lack of responsive support structures weakened the perceived value of HIS, thereby impeding adoption. These issues are further complicated by institutional inertia and lack of readiness for digital transformation, as noted by [36] who concluded that digital health policies in Tanzania often suffer from weak operationalization frameworks, limited resource allocation, and fragmented monitoring systems.

While there is a growing body of HIS research in Tanzania, many studies are limited in scope, often relying on qualitative or descriptive designs. There is a noticeable gap in theory based, statistically validated studies that explore the causal pathways between constructs influencing HIS adoption. For example, very few studies have employed inferential techniques such as Structural Equation Modeling (SEM) or integrated multi theoretical frameworks to examine adoption behaviors across different user levels. As highlighted by [33], this methodological gap restricts the generalizability and utility of findings, particularly in informing national policy and institutional strategies.

Given these empirical gaps, the current study adopts an integrated theoretical framework combining UTAUT, the DeLone and McLean IS Success Model, and the Diffusion of Innovations theory. This allows for a multidimensional analysis of user behavior, system attributes, and organizational factors in the implementation of GOTHOMIS. Employing SEM on data collected from health professionals across multiple public hospitals, the study tests hypotheses on how constructs such as performance expectancy, effort expectancy, communication, compatibility, system quality, and facilitating conditions predict both behavioral intention and actual system use. By doing so, the study aims to produce contextually grounded, evidence based insights that can guide future HIS policy reforms and implementation strategies in Tanzania's public health sector.

3. METHODOLOGY

This section presents the research methodology adopted to investigate the determinants influencing the implementation of the (GOTHOMIS) in public healthcare institutions. A quantitative research approach was employed, using a cross-sectional survey design. This approach enabled the collection of data at a single point in time to examine relationships among multiple variables and test the hypothesized conceptual framework. The cross-sectional design is widely recognized for its effectiveness in providing empirical evidence on associations between variables without the need for longitudinal follow-up, making it suitable for policy-driven and institutional studies in healthcare [37]. The choice of a quantitative approach was informed by the study's aim to objectively measure constructs, ensure comparability across respondents, and enable the application of advanced statistical modeling techniques for hypothesis testing.

3.1 Sampling

Please The target population comprised 1,438 healthcare professionals drawn from public hospitals located in Dar es Salaam, Dodoma, and Arusha, representing departments such as internal medicine, pediatrics, emergency, midwifery, surgical, and neonatal care [38]. These three regions were purposively selected due to their strategic relevance to Tanzania's healthcare system Dar es Salaam as the country's largest urban health and referral hub, Dodoma as the political capital hosting national government and policy institutions, and Arusha as a key regional center known for its robust tourism industry and status as the headquarters of the East African Community (EAC). In accordance with ethical clearance requirements, the specific names of the hospitals have been withheld to preserve institutional confidentiality. To determine the minimum sample size, Slovin's formula was applied at a 95% confidence level and a 5% margin of error, yielding a calculated sample size of 589 respondents [39]

To ensure representativeness and reduce sampling bias, the study employed a stratified random sampling technique. Each hospital department was treated as a distinct stratum, from which respondents were randomly selected in proportion to departmental size. This approach was chosen because it ensures that all relevant subgroups within the healthcare workforce such as nurses, doctors, pharmacists, and administrative personnel are adequately represented in the sample. Stratified sampling is particularly appropriate in healthcare studies, where roles, responsibilities, and levels of interaction with information systems vary significantly across departments and cadres [40]. By capturing this diversity, the technique enhances the internal validity of the findings and supports generalizability to the broader population of public healthcare professionals. A total of 589 questionnaires were distributed, and 405 were returned complete and valid, yielding a response rate of 68.9%.

3.2 Data Collection Methods

Primary data were gathered using a structured, self-administered questionnaire, which was deemed appropriate for this study due to its ability to standardize responses across a large and geographically dispersed sample. This method enables the efficient collection of quantifiable data while minimizing interviewer bias and allowing respondents the flexibility to complete the instrument at their convenience [37] The questionnaire was carefully designed based on established theoretical constructs drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT), the DeLone and McLean IS Success Model, and the Diffusion of Innovations

Theory [26]. These frameworks were selected because they collectively address the behavioral, technical, and contextual dimensions of technology adoption particularly relevant in the public healthcare setting.

To ensure clarity, relevance, and reliability of the instrument, a pilot study was conducted prior to full scale data collection. The pilot involved a small sample of healthcare professionals from a facility not included in the main study. Feedback from the pilot phase was used to refine question wording, eliminate ambiguities, and confirm the internal consistency of the constructs. This process strengthened the instrument's validity and ensured its suitability for the study context. The data collection period spanned from December 2024 to February 2025, providing adequate time for distribution, completion, and follow up in line with hospital workflows and ethical protocols.

3.3 Data Analysis

Quantitative data analysis was conducted using Statistical Package for the Social Sciences (SPSS) for initial processing and Structural Equation Modeling (SEM) for hypothesis testing. SPSS facilitated data cleaning, coding, and computation of descriptive statistics to profile respondents and summarize system usage trends [11].

To assess the validity of the measurement instrument, Exploratory Factor Analysis (EFA) was performed using Principal Component Analysis (PCA) with direct oblimin rotation. This method allows for correlated factors and is suitable for reducing dimensionality, identifying factor structures, and eliminating items with weak (<0.50) or cross-loadings [42].

Following EFA, Structural Equation Modeling (SEM) was applied using the maximum likelihood estimation method to test the hypothesized relationships among latent constructs. SEM was chosen for its ability to integrate factor analysis and multiple regression, thus enabling the assessment of both direct and indirect effects among constructs. This analytical approach is widely used in technology adoption studies for its robustness in evaluating complex, multi-variable models [41].

During measurement reliability testing, the construct Performance Expectancy (PE) demonstrated poor psychometric properties, with item loadings below 0.50 and a Cronbach's alpha below the recommended 0.70 threshold [43]. In accordance with construct purification principles [44], PE was excluded from the final SEM analysis to preserve model validity and improve goodness-of-fit indices. This decision reduced measurement error, improved path accuracy, and ensured that the model retained only statistically reliable constructs [45].

3.4 Quality Procedures

To ensure methodological rigor, several quality control procedures were implemented. Content validity was established through expert reviews by professionals in health informatics and ICT, who assessed the alignment between the instrument and the research objectives [45]. Reliability was evaluated using Cronbach's alpha, with all constructs exceeding the recommended threshold of 0.70, indicating strong internal [19] and [45]

Convergent validity was confirmed by assessing Composite Reliability (CR) and Average Variance Extracted (AVE), both of which met the minimum thresholds of 0.70 and 0.50, respectively. Discriminant validity was assessed using the Fornell-Larcker criterion, which confirmed that each construct shared more variance with its indicators than with other constructs [1]. In addition, Ethical considerations were upheld according to international standards. Ethical clearance was obtained from the participating hospitals. All respondents were informed of the voluntary nature of participation, and confidentiality was maintained through coded questionnaires and secure data handling practices [45].

4. RESULTS

This section presents the empirical findings of the study based on the data collected from healthcare professionals across selected public hospitals in Tanzania. The objective of this analysis was to examine the determinants influencing the implementation of the (GOTHOMIS) by applying statistical techniques aligned with the conceptual framework drawn from UTAUT, the DeLone and McLean IS Success Model, and the Diffusion of Innovations Theory.

4.1 Findings Presentation

4.1.1 Sample and Data Collection

Data were collected over a period of two months. Questionnaires were distributed across various departments in selected public hospitals to allow healthcare professionals time to respond. Out of 589 distributed questionnaires, 405 were valid and used for analysis, yielding a response rate of 68.9%.

4.1.2 Reliability Analysis

In the context of this study, reliability analysis was conducted to ensure the internal consistency of the measurement items for each construct. Cronbach's alpha was used to assess reliability. The acceptable threshold was set at 0.70. Table 1 below shows the reliability results.

Table 1. Reliability Analysis

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of Items	Acceptance Level
0.931	0.928	97	Good

The reliability analysis yielded a Cronbach's Alpha of 0.931, which indicates excellent internal consistency among the measurement items used in the study. This means that the items designed to measure the underlying constructs are highly correlated and consistently reflect the same latent variable.

The Cronbach's Alpha Based on Standardized Items (0.928) reinforces the robustness of the scale, suggesting that even after standardization, the internal consistency remains exceptionally strong.

4.1.3 Descriptive Statistics of constructs

Descriptive statistics were calculated to summarize responses on GOTHOMIS adoption determinants. Table 2 displays the minimum, maximum, mean, and skewness values.

The descriptive statistics reveal a consistently positive perception among healthcare professionals regarding the determinants of GOTHOMIS adoption. All constructs recorded a mean score of 4 on a five-point Likert scale, indicating general agreement with the statements presented. This suggests that respondents view the system as useful, easy to use, well-supported, and compatible with their work processes. The skewness values for most constructs are slightly negative, implying that responses are skewed toward the higher end of the scale reflecting strong support for the system's implementation. Constructs such as effort expectancy, user

attitude, and behavioral intention demonstrate particularly strong consensus, reinforcing the likelihood of sustained system use. The near-symmetrical skewness for constructs like service quality, system quality, and communication indicates balanced perceptions without extreme variation. Overall, the results suggest a highly favorable environment for the continued adoption and integration of GOTHOMIS in Tanzania's public healthcare system.

Table 2. Descriptive Statistics of constructs

Construct	Min	Max	Mean	Skew
Effort expectancy	2	5	4	-0.52
Performance expectancy	2	5	4	0.308
Social influence	2	5	4	-0.272
Facilitating conditions	2	5	4	-0.196
Behavioural intention	2	5	4	-0.212
User attitude	2	5	4	-0.457
Service quality	2	5	4	-0.001
System use	2	5	4	-0.156
Information quality	2	5	4	-0.26
User satisfaction	2	5	4	-0.163
System quality	1	5	4	-0.015
Communication	2	5	4	0.001
Compatibility	2	5	4	-0.123
Trialability	2	5	4	-0.056
GOTHOMIS Implementation	2	5	4	-0.223

4.1.4 Exploratory Factor Analysis

EFA was conducted using Principal Component Analysis (PCA) with direct oblimin rotation. The Kaiser–Meyer–Olkin (KMO) measure was 0.950, indicating superb sampling adequacy. Bartlett's Test of Sphericity was significant (χ^2 = 20228.311, df = 1485, $p < 0.001$), justifying the factor analysis.

Table 3. Exploratory Factor Analysis

Test	variable	Value
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.950
Bartlett's Test of Sphericity -	Approx. Chi-Square	20228.311
	Degrees of Freedom (df)	1485
	Significance (Sig.)	0.000

The results of the Exploratory Factor Analysis (EFA) confirm the appropriateness of applying factor analysis to the dataset. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.950, which falls within the "superb" range, indicating that the sample size was more than adequate and the variables shared sufficient common variance for reliable factor extraction. Additionally, Bartlett's Test of Sphericity was statistically significant (χ^2 = 20228.311, df = 1485, $p < 0.001$), demonstrating that the correlation matrix is not an identity matrix and that the variables are sufficiently interrelated to justify the use of factor analysis. Together, these results provide strong statistical support for proceeding with factor analysis and suggest that the extracted factors are likely to be valid and meaningful representations of the underlying constructs in the dataset.

The following table displays the complete pattern matrix extracted through exploratory factor analysis (EFA) for GOTHOMIS adoption study in Tanzania's public healthcare system. Full item labels have been used for interpretive clarity

The factor analysis revealed a robust 14-factor structure underpinning the adoption of GOTHOMIS in Tanzania's public healthcare system, confirming the theoretical model's multidimensional nature. Key constructs such as Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention emerged with high factor loadings, indicating that users perceive GOTHOMIS as easy to use, supported by peers and supervisors, and well-facilitated by hospital infrastructure. User Attitude and System Quality also showed strong explanatory power, reflecting favorable emotional responses and confidence in the system's reliability. Constructs like System Use, Information Quality, and User Satisfaction demonstrated that GOTHOMIS is actively integrated into healthcare routines, with users appreciating the accuracy and utility of the data it provides. Compatibility and Communication factors highlighted the system's fit within existing workflows and the effectiveness of internal awareness campaigns. Trialability and Implementation Context further revealed that allowing users to experiment with the system and providing a supportive deployment environment are important to successful adoption. Overall, the analysis affirms the conceptual model and underscores the importance of both technical performance and organizational support in driving GOTHOMIS acceptance. Table 5 present the data.

4.1.5 Hypotheses Testing Using SEM

Structural Equation Modeling (SEM) was employed to test fifteen hypotheses regarding factors influencing the implementation of GOTHOMIS, with results summarized in Table 5. Out of the thirteen tested hypotheses (excluding H2, which was dropped due to low reliability), seven were supported by the model. Hypothesis H1, which posited that Effort Expectancy (EE) impacts implementation, was not supported ($\beta = -0.573$, $p = 0.862$), indicating no significant relationship. Similarly, H3 and H4, which assessed the influence of Social Influence (SI) and Facilitating Conditions (FC), were also unsupported ($\beta = -0.054$, $p = 0.882$; $\beta = -0.213$, $p = 0.840$, respectively). Hypothesis H5, which linked Behavioral Intention (BI) to implementation, was supported ($\beta = -0.209$, $p < 0.001$), suggesting a statistically significant but inverse relationship. Hypotheses H6 and H7 concerning User Attitude (UA) and User Satisfaction (US) were not supported ($\beta = 0.478$, $p = 0.741$; $\beta = -0.317$, $p = 0.937$), indicating that users' feelings toward the system and their satisfaction did not predict implementation outcomes.

In contrast, hypotheses H8 through H13 were all supported, indicating that System Use ($\beta = 0.209$, $p < 0.001$), Information Quality ($\beta = 0.557$, $p < 0.001$), Service Quality ($\beta = 0.563$, $p < 0.001$), Communication ($\beta = 0.211$, $p < 0.001$), Compatibility ($\beta = 0.419$, $p < 0.001$), and Trialability ($\beta = -0.019$, $p < 0.001$) significantly influenced implementation. Notably, Trialability had a negative relationship, suggesting that increased experimentation may have introduced concerns or resistance affecting implementation outcomes. Overall, the model demonstrated strong explanatory power with an R^2 value of 0.75 across all relationships.

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Table 4. Hypothesis Tasting

Hypothesis	Relationship	Standardized Estimate	SE	CR	p-value	Decision
H1	IM< EE	-0.573	0.026	0.174	0.862	Unsupported
H2	IM< PE	Dropped	-	-	-	Dropped
H3	IM< SI	-0.054	0.032	0.148	0.882	Unsupported
H4	IM< FC	-0.213	0.023	0.203	0.840	Unsupported
H5	IM< BI	-0.209	0.063	-5.287	<0.001	Supported
H6	IM<UA	0.478	0.019	0.331	0.741	Unsupported
H7	IM< US	-0.317	0.028	0.076	0.937	Unsupported
H8	IM< SU	0.209	0.029	5.363	<0.001	Supported
H9	IM< IQ	0.557	0.047	8.883	<0.001	Supported
H10	IM< SQ	0.563	0.032	6.436	<0.001	Supported
H11	IM < C	0.211	0.046	7.538	<0.001	Supported
H12	IM< CP	0.419	0.081	6.015	<0.001	Supported
H13	IM< TR	-0.019	0.090	7.437	<0.001	Supported

Table 5: The 14 Factor Pattern Matrix

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14
EF5.	0.853													
EF2	0.806													
EF4														
SO5		0.417												
SO3		0.837												
SO1		0.786												
FA6			0.813											
FA5			0.337											
FA3.			0.859											
FA2			0.803											
FA1			0.648											
BI5				0.538										
BI3				0.839										
BI2				0.718										
BI1				0.797										
UA5					0.813									
UA4					0.508									
UA3					0.638									
UA1					0.774									
SY6						0.772								
SY4						0.452								
SY3						0.744								
SY2						0.702								
SU1							0.793							
SU4							0.707							
SU5							0.556							
IN1								0.610						
IN3								0.771						
IN5								0.708						
US2									0.686					
US4									0.583					
US6									0.790					
IN6														
SYQ2										0.293				
SYQ3										0.343				
SYQ6										0.377				
SYQ4											0.372			
CO1											0.762			
CP2												0.552		
CP4												0.713		
CP6												0.873		
TR1													0.610	
TR2													0.767	

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14
TR4													0.683	
TR6													0.702	
IM1														0.840
IM2														0.380
IM3														0.330
IM5														0.802
IM6														0.653

5. DISCUSSION OF FINDINGS

This study provides robust empirical insights into the multifaceted factors shaping the successful implementation of the (GOTHOMIS). By integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), DeLone and McLean's Information Systems Success Model, and the Diffusion of Innovations theory, the study offers a comprehensive framework that captures both individual and institutional-level influences. The statistically significant constructs Information Quality, Service Quality, Communication, Compatibility, System Use, Behavioral Intention, and Trialability collectively underscore the importance of aligning technological interventions with contextual realities in Tanzania's public healthcare infrastructure.

This study's empirical analysis reveals that Information Quality ($\beta = 0.557$, $p < 0.001$) and Service Quality ($\beta = 0.563$, $p < 0.001$) are the most potent predictors of GOTHOMIS implementation, findings that are deeply congruent with current literature. Across low- and middle-income countries, the quality of clinical information its completeness, timeliness, and accuracy has been repeatedly affirmed as the bedrock of successful health information system deployment [46]. In the Tanzanian context, where health workers are overburdened and accountability frameworks are still evolving, data quality does more than facilitate care it serves as a proxy for institutional trust and operational legitimacy. Likewise, the positive impact of service quality, particularly user training, system responsiveness, and technical troubleshooting, corroborates studies such as those by [47] and [48], which emphasize that ICT interventions devoid of consistent user support are likely to fail, regardless of their technical sophistication. These findings collectively affirm that institutional investments must prioritize not only hardware and software but also the intangible dimensions of system credibility and user trust.

The significance of Communication ($\beta = 0.211$, $p < 0.001$) as a determinant underscore a dimension that remains under-theorized in mainstream ICT adoption models. While traditional frameworks such as TAM and UTAUT often reduce communication to a moderating variable or ignore it altogether, emerging organizational change literature positions it as a fundamental catalyst of behavioral alignment [49] and [50]. Communication in this study encompassed clarity of purpose, frequency of updates, and transparency in implementation a triad that, when absent, tends to induce ambiguity, alienation, and ultimately resistance among system users. This echo [37] proposition that robust communication is not merely informative but dialogic; it shapes mental models and fosters psychological ownership. In the Tanzanian hospital setting, where top-down implementation is prevalent, this finding mandates a shift towards more participatory, feedback-driven implementation models.

The high significance of Compatibility ($\beta = 0.419$, $p < 0.001$) further reinforces the enduring validity of Rogers' Diffusion of Innovations theory, particularly the construct that technologies are more likely to be adopted when they align with existing values, practices, and workflows [12]. This is not merely a matter of technical interoperability but of socio-organizational coherence. Studies by [51] and [52] demonstrate that digital health systems perceived as disruptive to routine practices are often rejected, regardless of their potential utility. In Tanzanian public hospitals, where staffing is lean and administrative duties are intensive, systems that require excessive new learning or procedural overhaul are naturally met with skepticism. Thus, this result affirms that system design must be locally grounded and co-produced with end users, not imposed through standardized, top-down modules.

System Use ($\beta = 0.209$, $p < 0.001$) also emerged as a statistically significant predictor, which aligns with classical IS success models that position use as both an outcome and an antecedent of net system benefits [53]. However, the nuance lies in how usage is framed.

In this study, system use was not purely volitional but was influenced by infrastructural affordances electricity availability, server uptime, terminal functionality concerns echoed in literature by [18], [54] and [55]. Therefore, while frequency of system interaction indicates increasing operational integration, it is also a function of resource stability and institutional support. This compels a reinterpretation of use not merely as a behavioral construct, but as an infrastructural indicator.

Conversely, the negative and significant effect of Behavioral Intention ($\beta = -0.209$, $p < 0.001$) challenges one of the core assumptions of UTAUT that intention precedes and predicts use [56]. The Tanzanian data suggest that behavioral intention may be inflated or performative, shaped more by administrative expectations or social desirability than by genuine readiness. This aligns with [57] findings that in hierarchical healthcare environments, users may express acceptance to avoid sanctions or to align with institutional rhetoric. Furthermore, systemic inhibitors such as network downtime or inadequate terminals render intention moot when the physical environment prevents enactment. Hence, this finding invites an important rethinking of intention as an inherently contextual construct that must be situated within broader socio-technical ecosystems, rather than treated as a universal precursor to use.

The negative association with Trialability ($\beta = -0.019$, $p < 0.001$), though modest in magnitude, is theoretically consequential. While trialability is traditionally viewed as a facilitator enabling users to experiment without commitment [12] evidence suggests that when trial versions are incomplete, poorly supported, or inconsistently implemented, they generate early disillusionment that persists into full deployment [37]. In the case of GOTHOMIS, several pilot sites reported irregular training, inadequate help desks, and inconsistent software functionality, all of which likely eroded initial confidence. This finding affirms that pilot phases are not neutral they either build credibility or seed skepticism. Thus, pilot design must be resource-intensive, user-centered, and iterative, not tokenistic.

Notably, the negative and significant path coefficient for Behavioral Intention ($\beta = -0.209$, $p < 0.001$) deviates from the conventional assumptions of the UTAUT model, where intention is expected to positively influence actual use. One possible explanation lies in contextual constraints that prevent intention from translating into action such as poor infrastructure, limited access to ICT terminals, or lack of institutional enforcement. In such environments, healthcare workers may express favorable intentions in principle but remain unable or unwilling to act due to systemic barriers [58] and [46]. Another plausible explanation involves social desirability bias or performative compliance, where respondents report positive attitudes due to hierarchical expectations or fear of non-conformity in public institutions [57] Additionally, suppressor effects may be at play where the inclusion of correlated predictors (e.g., system use or service quality) modifies the apparent influence of intention by capturing overlapping variance [52]. These findings underscore the need to treat behavioral intention as a context-dependent construct, especially in resource-constrained public health systems where structural limitations often override individual volition.

Finally, the insignificance of constructs such as Effort Expectancy, Facilitating Conditions, Social Influence, User Attitude, and User Satisfaction may reflect the overriding influence of institutional constraints in the Tanzanian context. While these variables are central in Western-dominated adoption literature, studies in Sub-Saharan Africa increasingly show that macro-structural conditions such as political will, funding stability, and governance culture determine ICT outcomes more decisively than user perceptions [58] and [59]. For instance, even the most user-friendly system fails when staff lack access to computers or electricity. This divergence suggests that future frameworks should shift from purely cognitive models toward integrated socio-technical paradigms that recognize the interdependence of people, systems, and institutional environments.

6. CONCLUSION AND RECOMMENDATIONS

This study investigated the determinants influencing the successful implementation of GOTHOMIS (Government of Tanzania Hospital Management System) in public healthcare institutions. Through the application of Exploratory Factor Analysis and Structural Equation Modeling, the study confirmed the significance of seven key predictors: Information Quality, Service Quality, System Use, Communication, Compatibility, Behavioral Intention, and Trialability. The integration of UTAUT, the DeLone and McLean IS Success Model, and the Diffusion of Innovations theory provided a robust framework for understanding the dynamics of health ICT adoption in a developing country context.

The results revealed that high quality information and effective service support are the most influential factors, underscoring the importance of data integrity and responsive user support. Furthermore, the findings emphasized that alignment of the system with existing workflows (compatibility), clear communication strategies, and sustained system usage are important to ensuring implementation success. Contrarily, traditionally influential constructs such as Effort Expectancy, Social Influence, and Facilitating Conditions showed no significant impact in this context, suggesting that structural and institutional constraints outweigh individual perceptions in Tanzania's public healthcare setting. These insights are important for improving current implementation strategies and guiding future digital health interventions.

As part of recommendations, the Ministry of Health should prioritize investment in digital health infrastructure across public hospitals. The study confirmed that system use and compatibility significantly influence the implementation of GOTHOMIS. However, many institutions suffer from limited connectivity, unstable power supply, and outdated equipment, which restrict system effectiveness. Therefore, the Ministry should provide consistent funding for internet services, power backup systems, and equipment maintenance. Such investment will help bridge the gap between healthcare professionals' intention to use the system and their actual ability to do so, enhancing both usability and reliability in day to day operations.

The GOTHOMIS Implementation Team, under the Ministry of Health and ICT experts, should design and conduct user centered pilot phases before national rollout. The study revealed a negative impact of trialability on system adoption, suggesting that early exposure without proper support led to user dissatisfaction. To counter this, implementation teams must adopt a participatory approach that allows healthcare workers to test the system under realistic conditions. This includes running simulations, holding guided sessions, collecting feedback, and iteratively improving system features before full deployment. Structured piloting will reduce errors, increase user trust, and improve adoption rates.

For ICT departments within public hospitals, the focus should be on establishing responsive technical support systems and continuous training programs. The strong positive influence of both service quality and information quality indicates that healthcare professionals value support services and accurate system output. ICT units must ensure that users can easily access technical assistance when facing challenges. Moreover, training sessions should be scheduled regularly, not just during system installation. These sessions should be tailored to varying user competencies and should emphasize hands on practice, data accuracy, and confidentiality procedures.

Hospital administrators must ensure that GOTHOMIS is effectively integrated into existing workflows rather than being imposed as an external tool. The construct of compatibility was one of the strongest predictors of adoption, indicating that users are more likely to accept systems that reflect their daily routines. Administrators should involve medical staff in the customization process to align GOTHOMIS modules with local health procedures. Clear mapping between current paper based practices and the new digital equivalents should be communicated and supported by change management strategies to build ownership and reduce resistance.

It is essential for policy makers and regulatory bodies, such as the Tanzania e Government Authority (eGA) and the President's Office – Public Service Management, to formulate and enforce national guidelines that support digital health implementation. These should cover data standards, access protocols, and system performance monitoring. Given the significant role of communication and behavioral intention in the model, coherent policies will promote clarity, reduce uncertainty, and ensure that both healthcare workers and administrators operate under a shared vision. Policy frameworks should also define accountability structures and promote compliance across institutions.

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