ORIGINAL RESEARCH

# Key Factors Influencing Intention to Use Digital Health Systems Among Healthcare Workers in Malawi

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## Abstract

### Introduction

Digital Health systems (DHS) have the potential to strengthen healthcare delivery, yet their adoption remains limited in many low- and middle-income countries. Despite progress in digital health implementation, Malawi continues to face challenges related to effective use of DHS. This study investigates the key factors influencing healthcare workers' intention to use DHS in Malawi.

### Methods

This was a cross-sectional quantitative design that used a structured questionnaire to collect data from a sample of 615 healthcare workers across Malawi. Factor analysis and reliability testing were conducted to assess construct validity and internal consistency. Multiple linear regression was used to identify factors influencing intention to use DHS, while generalized structural equation modelling (GSEM) examined relationships involving categorical variables.

### Results

The results indicated that healthcare workers' intention to use DHS is influenced by several factors including, perceived ease of use ($\beta = 0.358$, $p < 0.001$), perceived usefulness ($\beta = 0.284$, $p = 0.001$), job relevance ($\beta = 0.274$, $p = 0.001$) and subjective norms ($\beta = 0.127$, $p < 0.001$). These findings suggest that healthcare workers are more likely to use DHS when they perceive them as useful, relevant to their daily work, easy to use, and are supported by their peers. In contrast, computer anxiety indicated a significant negative effect ($\beta = -0.061$, $p = 0.001$), suggesting that higher levels of computer anxiety reduce the likelihood of DHS use. Demographic and contextual factors, including gender, age, and education level were not significant factors influencing DHS.

### Conclusion

These findings highlight the importance of aligning digital health systems with healthcare workers' job roles, ensuring system usability, and leveraging social influence to promote adoption. Addressing computer anxiety through targeted training and capacity building may also enhance digital confidence and sustained system use.

**Keywords:** Digital health systems, Technology Acceptance Model, Healthcare workers, Malawi, Technology adoption.

## Introduction

Innovation is widely recognised as a major driver for long-term economic growth and sustainable development, accounting for an estimated 60 percent of productivity growth in high income economies and contributing substantially to development gains in low and middle-income countries[1]. Technological innovation in the healthcare sector has been associated with measurable improvements in health outcomes and system performance. Digital health technologies, including health information systems, can reduce medical errors by approximately 30 percent, improve clinical decision making, and lower administrative and operational costs by between 10 and 25 percent when effectively implemented[2,3]. Global investment in digital health systems has increased rapidly in recent years, exceeding USD 200 billion between 2016 and 2022, reflecting growing recognition of the role of digital technologies in improving life expectancy, quality of care, service coverage, and cost effectiveness of healthcare systems[3]. Evidently, digital health systems are central to these advances, as they support routine data collection, analysis, and use for health system planning, monitoring, and service delivery.

Despite their demonstrated potential, the implementation and sustained use of digital health systems continue to face substantial social, organizational, and technological constraints, particularly in low- and middle-income countries[3]. Evidence suggests that more than half of digital health system initiatives in low resource settings fail to progress beyond the pilot stage or achieve long-term sustainability[4]. Persistent barriers include inadequate information and communication technology infrastructure, limited financial resources, shortages of trained health personnel, and weak institutional capacity to support system integration and maintenance[5]. These challenges are often compounded by rapidly growing service demand and constrained health system financing, limiting the ability of health systems to absorb and scale digital innovations.

Malawi has made measurable progress in advancing digital health initiatives, including the introduction of electronic medical records and routine health information platforms. However, national assessments indicate that the health system remains highly dependent on paper-based reporting, with



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digital solutions covering only a portion of health facilities and services[6]. Key challenges include limited sustainability of digital health solutions, inadequate system interoperability, weak coordination of digital health efforts, and persistent concerns regarding data quality and system reliability[6]. These constraints reduce confidence in digital platforms among healthcare workers and limit the routine use of digital health systems in clinical and administrative decision making.

While technology acceptance and digital health adoption have been extensively examined in high income settings, empirical evidence on healthcare workers' behavioural determinants of digital health system adoption in Malawi remains limited. This gap is particularly important given the distinct institutional, economic, and infrastructural conditions under which digital health systems are introduced in Malawi. Unlike developed health systems where digital technologies are integrated into well-established infrastructures, digital health systems in Malawi are implemented alongside broader system constraints, including workforce shortages and limited technical support. As a result, adoption dynamics are shaped not only by system availability but also by healthcare workers' perceptions, attitudes, and experiences with technology.

Existing evidence from low- and middle-income countries indicates that user related factors such as perceived usefulness, perceived ease of use, job relevance, and social influence play a critical role in shaping behavioural intention to use digital health systems[5]. Studies from similar contexts, including Nigeria and other developing countries, show that technology related anxiety and limited digital skills significantly reduce healthcare professionals' willingness to adopt and use digital systems[1,3]. The World Health Organization similarly emphasises that successful digital health transformation depends on contextual adaptation, stakeholder engagement, and user centred system design, highlighting the importance of understanding local determinants of digital health system adoption[3].

Despite the strategic importance of digital health in Malawi, empirical evidence on the factors that influence healthcare workers' intention to use digital health systems remains limited[6]. This evidence gap constrains the design and sustainability of digital health interventions, many of which are implemented without sufficient consideration of user behaviour and contextual realities. In response, this study aims to identify the key factors influencing healthcare workers' intention to use digital health systems in Malawi. By generating context specific evidence on behavioural and organizational factors affecting adoption, the study seeks to inform the sustainable integration of digital health systems within Malawi's health system. The findings of this study contributes to the design and successful implementation of digital health systems that are scalable in the context of Malawi and other low resource countries.

## Method And Materials

### *Study design, and Study setting*

This study employed a cross-sectional quantitative design. The study was conducted in Malawi, a low-income country in Southern Africa with a decentralised health system comprising of primary, secondary, and tertiary healthcare facilities distributed across three administrative regions, namely, Northern, Central, and Southern regions.

### *Study population and sampling*

The unit of analysis was the individual healthcare worker, and the study population comprised healthcare workers drawn from public and private health facilities across all three regions. A stratified sampling approach was used to ensure proportional regional representation. Simple random sampling was applied in each stratum (confidence level of 95%, z – score of 1.96, margin of error of 5% and standard deviation of 0.5) yielding a total sample size of 615 participants comprising 180 drawn from the Northern region, 180 from the Central region, and 255 from the Southern region.

### *Study period*

Data was collected from April to September 2025.

### *Variables and Measurement*

The primary outcome variable in this study was healthcare workers' intention to use digital health systems, measured using a multi-item scale adapted from the TAM2 to capture respondents' willingness and readiness to adopt and routinely use digital health systems. Explanatory variables were selected based on established technology acceptance literature which included Perceived Usefulness (PU), Perceived Ease of Use (PEU), Job Relevance (JR), Subjective Norm (SN), Descriptive Norm (DN), Computer Anxiety (CA), and facilitating conditions including Computer Use (CU) and training[7-11]. Perceived usefulness and perceived ease of use measured beliefs about performance enhancement and system usability, respectively, while job relevance captured the applicability of digital health systems to routine work tasks. Social influence was assessed using subjective norm and descriptive norm, reflecting perceived expectations from colleagues and perceptions of peer system use. Computer anxiety measured discomfort associated with computer use, and facilitating conditions were captured through indicators of prior computer or digital health training and frequency of computer use. All constructs were measured using validated multi-item scales on a seven-point Likert scale. Demographic and contextual variables were included as controls. A summary of all variables and their measurement is presented in Table 1. Composite scores were computed by averaging item responses for use in the regression analyses.

### *Data collection*

Data were collected using a structured questionnaire administered electronically through the Kobo Toolbox platform, informed by established literature on technology acceptance. Responses were measured using a seven-point Likert scale ranging from strongly disagree to strongly agree, allowing for detailed assessment of healthcare workers' perceptions and intentions regarding the use of digital health systems.

### *Ethical Considerations*

The study was carried out following ethical rules and guidelines. Ethical clearance was obtained from the Malawi University of Science and Technology Research and Ethics Committee (MUSTREC) with ethical reference number P.04/2025/352. Informed consent was obtained from participants prior to participation in the study. The data complies with all provisions of the data privacy act of Malawi.

### *Data analysis*

The empirical analysis was guided by the Technology Acceptance Model 1 and Technology Acceptance Model 2, which provide a robust theoretical basis for modelling behavioural intention to use digital health systems in organizational and healthcare settings[8,11-15]. Healthcare workers' intention to use digital health systems was specified as the dependent variable and modelled as a function of cognitive beliefs, social influence, behavioural inhibitors, facilitating conditions, and individual characteristics.The baseline empirical model was estimated to use multiple linear regression and is specified as:

$$IU_i=\beta_0+\beta_1 PU_i+\beta_2 PEU_i+\beta_3 JR_i+\beta_4 SN_i+\beta_5 CA_i+\beta_6 CU_i+Z_i \gamma+\varepsilon_i \quad (1)$$

where $IU_i$ denotes the intention to use digital health systems by healthcare worker; $PU_i$ represents perceived usefulness; $PEUi$ denotes perceived ease of use; $JR_i$ captures job relevance; $SN_i$ represents subjective norm; $CA_i$ denotes computer anxiety; and $CU_i$ represents computer use.

$Z_i$ is a vector of control variables including age, gender, education level, region, and years of work experience.

**Table 1 Description of variables and measurement**

| Variable | Description |
|---|---|
| Intention to use | Willingness and readiness to adopt and use digital health systems |
| Perceived usefulness | Belief that DHS improves job performance, productivity, and effectiveness |
| Perceived ease of use | Perceived effort required to learn and operate DHS |
| Job relevance | Applicability of DHS to routine work tasks |
| Subjective norm | Perceived social pressure from colleagues and supervisors to use DHS |
| Descriptive norm | Perception that peers and colleagues use DHS |
| Computer anxiety | Discomfort or fear associated with computer use |
| Computer training (yes, no*) | Prior formal training in computers or digital health systems |
| Computer use (frequent, infrequent*) | Previous computer usage |
| Age (years) | Age of healthcare worker |
| Gender (male, female*) | Biological sex |
| Education level (certificate*, diploma, degree and above) | Highest education level attained |
| Professional cadre | Clinical or administrative role |
| Region (Northern, Central, Southern) | Region of workplace |
| Work experience (years) | Years of professional experience |

*Note: Categories marked with an asterisk indicate the reference group used in the regression analysis.*

**Table 2 Demographic Characteristics**

| Demographic Characteristics | Count (n=615) | Percent (%) |
|---|---|---|
| Gender | | |
| Male | 297 | 48.29 |
| Female | 318 | 51.71 |
| Age (years) | | |
| 18-25 years | 78 | 12.68 |
| 26-35 years | 339 | 55.12 |
| 36-50 years | 180 | 29.27 |
| 51+ years | 18 | 2.93 |
| Education Level | | |
| Junior school certificate | 6 | 0.98 |
| High school certificate | 84 | 13.66 |
| College certificate | 27 | 4.39 |
| Diploma | 261 | 42.44 |
| Degree/Honors degree | 210 | 34.15 |
| Masters/PhD | 23 | 3.74 |
| Others | 4 | 0.65 |
| Work experience | | |
| 1-5 years | 312 | 50.73 |
| 6-10 years | 143 | 23.25 |
| 11-15 years | 86 | 13.98 |
| 16+ years | 74 | 12.03 |
| Region | | |
| Central Region | 180 | 29.30 |
| Northern Region | 180 | 29.30 |
| Southern Region | 255 | 41.40 |

This specification is consistent with prior empirical applications of TAM 1 and TAM2 in digital health system research[7,16,17].

To examine the robustness of the linear regression results and to account for categorical predictors and latent constructs, a Generalized Structural Equation Modelling (GSEM) framework was also employed. GSEM is well suited for analysing complex behavioural models involving variables with mixed measurement scales and has been increasingly applied in digital health adoption studies[8,18].

Within the GSEM framework, intention to use digital health systems was specified as a latent index influenced by key behavioural constructs and demographic and contextual characteristics, as expressed by:

$$IU_i^*=\alpha_0+\alpha_1 PU_i+\alpha_2 PEU_i+\alpha_3 CA_i+D_i \delta+\varepsilon_i \quad (2)$$

where $IU_i^*$ denotes the latent intention to use digital health systems for healthcare worker i; $PUi$ and $PEU_i$ represent perceived usefulness and perceived ease of use, respectively; and $CA_i$ captures computer anxiety. $D_i$ is a vector of observed categorical variables including gender, age category, education level, work experience, training on digital health systems, computer access, and computer use. Base categories were specified for all categorical variables to allow meaningful comparisons across groups.

Statistical significance was evaluated at the 5 percent level.

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**Table 3 Factor loadings and reliability statistics for measurement constructs**

*Factor Loadings*

| | | | | | | 95% Confidence interval | |
|---|---|---|---|---|---|---|---|
| Latent | Indicator | Std. estimate | Std. error | z-value | p | Lower | Upper |
| Perceived usefulness (PU) | Job Performance | 0.775 | 0.017 | 44.89 | < .001 | 0.741 | 0.809 |
| | Productivity | 0.918 | 0.008 | 114.39 | < .001 | 0.902 | 0.934 |
| | Effectiveness | 0.909 | 0.009 | 105.94 | < .001 | 0.892 | 0.926 |
| | Usefulness | 0.908 | 0.009 | 104.15 | < .001 | 0.891 | 0.925 |
| Job relevance (JR) | DHS is Important in my job | 0.750 | 0.024 | 30.95 | < .001 | 0.702 | 0.797 |
| | DHS is relevant in my job | 0.709 | 0.025 | 27.83 | < .001 | 0.659 | 0.759 |
| Perceived ease to use (PEU) | DHS are easy to Use | 0.891 | 0.011 | 83.10 | < .001 | 0.870 | 0.912 |
| | Easy to Understand | 0.897 | 0.010 | 86.07 | < .001 | 0.876 | 0.917 |
| | Easy to Control | 0.832 | 0.014 | 57.76 | < .001 | 0.804 | 0.860 |
| | Require Low Mental Effort | 0.591 | 0.028 | 21.24 | < .001 | 0.536 | 0.645 |
| Computer anxiety (CA) | Computer Make me feel uncomfortable | 0.792 | 0.028 | 27.94 | < .001 | 0.736 | 0.847 |
| | Computer are uneasy | 0.837 | 0.028 | 29.74 | < .001 | 0.782 | 0.892 |
| | Computer do not scare me at all | 0.539 | 0.034 | 15.97 | < .001 | 0.473 | 0.606 |
| Subjective norm (SN) | Supported by my colleague | 0.897 | 0.016 | 54.58 | < .001 | 0.865 | 0.929 |
| | Accepted by my colleague | 0.805 | 0.019 | 41.92 | < .001 | 0.767 | 0.843 |

**Table 4 Reliability statistics for study construct**

| | Coefficient α | Coefficient ω |
|---|---|---|
| PU | 0.929 | 0.926 |
| PEU | 0.868 | 0.864 |
| JR | 0.691 | 0.691 |
| CA | 0.753 | 0.760 |
| SN | 0.838 | 0.840 |
| Overall | 0.853 | 0.926 |

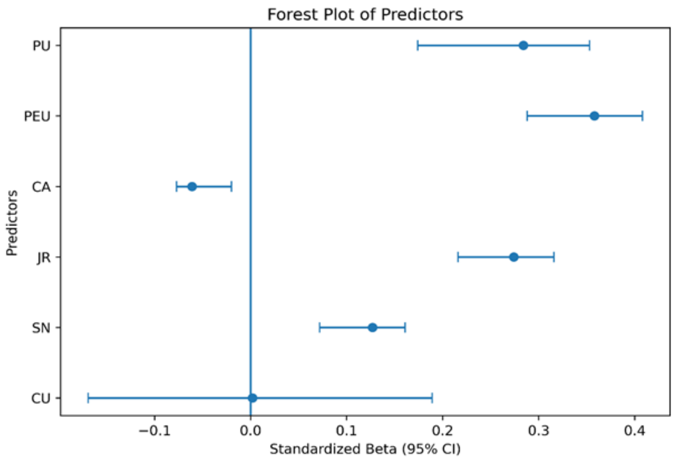


**Figure 1: Forest plot, multiple linear regression results for factors influencing intention to use digital health systems**

The linear regression and GSEM specifications provide a comprehensive empirical framework for identifying key determinants of healthcare workers' intention to use digital health systems in Malawi and ensure consistency with the study's theoretical and conceptual foundations.

# Results

## *Socio-demographic characteristics of respondents*

The study sample (n=615) comprised slightly more females (51.7%) than males (48.3%), with most participants aged between 26 and 35 years (55.1%), followed by those aged 36–50 years (29.3%). This indicates a predominantly young to mid-career workforce, which is typically more adaptable to new technologies. In terms of education, most respondents held a Diploma (42.4%) or a Degree/Honors degree (34.2%), suggesting a generally well-qualified group with the educational background to engage effectively with digital health systems.

Over half of the participants (50.7%) had 1–5 years of work experience, indicating a relatively early-career profile, while only 12% had more than 16 years in the profession. Regionally, nearly half of the sample came from the Southern Region (41.4%), followed by the Central (29.3%) and Northern (29.3%) regions. This distribution reflects possible regional differences in infrastructure and resource availability that may influence digital health system adoption readiness. Overall, the demographic profile suggests a workforce that is young, moderately experienced, and educationally equipped to engage with digital health system innovations.

## *Measurement Validity and Reliability*

Exploratory factor analysis was conducted to assess construct validity and the results are presented in Table 3, The results show that observed indicators exhibited strong and statistically significant factor loadings. Perceived usefulness indicators exhibited particularly high loadings, ranging from 0.775 to 0.918 ($p < 0.001$), while perceived ease of use indicators loaded between 0.591 and 0.897. Similarly, computer anxiety, job relevance, and subjective norm demonstrated statistically significant loadings with p values below 0.001. These results confirm the adequacy of the measurement model and strong convergent validity of the constructs. In the analysis, computer use, descriptive norms, and intention to use were modelled as observed variables. Reliability of the constructs for internal consistency of the measurement scales was conducted using Cronbach Alpha and the results are presented in Table 4. The results show that Cronbach's alpha coefficients ranged from 0.691 to 0.929. Perceived usefulness demonstrated excellent reliability ($\alpha = 0.929$), while perceived ease of use ($\alpha = 0.868$) and subjective norm ($\alpha = 0.838$) showed very good reliability. Computer anxiety ($\alpha = 0.753$) and job relevance ($\alpha = 0.691$). Overall, the reliability results indicate that the constructs were measured consistently and were suitable for regression analysis.

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**Table 5: Generalized structural equation modelling results for factors influencing intention to use digital health systems**

| Intention to adopt (index) | Coefficient | Std. err. | Z | p-value | Coefficient | Std. err. | Z | p-value |
|---|---|---|---|---|---|---|---|---|
| PU score | .2628552 | .0553391 | 4.75 | 0.000*** | .2628552 | .0553391 | 4.75 | 0.000*** |
| PEU score | .2995397 | .05539 | 5.41 | 0.000*** | .29953067 | .05539 | 5.41 | 0.000*** |
| CA score | -.1353067 | .0348385 | -3.88 | 0.000*** | -.1353067 | .348385 | -3.88 | 0.000*** |
| Gender | | | | | .025014 | .0687721 | 0.55 | 0.582 |
| Education | | | | | | | | |
| High school certificate | | | | | .222893 | .3559294 | 0.63 | 0.531 |
| College certificate | | | | | .2074931 | .3769656 | 0.55 | 0.582 |
| Diploma | | | | | .1675546 | .3527124 | 0.48 | 0.635 |
| Degree/ Honors degree | | | | | .3255221 | .3579128 | 0.91 | 0.363 |
| Masters/PhD | | | | | .1668539 | .3941119 | 0.68 | 0.498 |
| Age | | | | | | | | |
| 26-35 years | | | | | .0354376 | .1096872 | 0.32 | 0.747 |
| 36-50 years | | | | | .0857573 | .1407761 | 0.61 | 0.542 |
| 51+ years | | | | | -.1734464 | .2450487 | -0.71 | 0.479 |
| Working experience | | | | | | | | |
| 6-10 years | | | | | -1147852 | .0908055 | -1.26 | 0.206 |
| 11-15 years | | | | | -.2423336 | .1269755 | -1.91 | 0.056 |
| 16+ years | | | | | -.0110013 | .1508374 | -0.07 | 0.942 |
| Training on DHS | | | | | -.1639079 | .0730938 | -2.24 | 0.025 |
| Personal computer access at work | | | | | .0697071 | .073817 | 0.94 | 0.345 |
| Personal computer access at home | | | | | -.053749 | .0814432 | 0.66 | 0.509 |
| Use of a computer | | | | | .0093102 | .0069538 | 1.34 | 0.181 |

Notes: PU = Perceived Usefulness, PEU = Perceived Ease of Use, and CA = Computer Anxiety; Significance levels are indicated by *p < 0.01, p < 0.05 and *p < 0.10* for 1%, 5% and 10% significance, respectively; base categories are Junior school certificate for education, 18-25 years for age, 1-5 years for working experience, Female for gender, No for training on digital health system, personal computer access at work and home; the equation used is Generalized Structural Equation Modeling (GSEM).

## *Multiple Linear Regression Results*

Multiple linear regression analysis was conducted to identify factors influencing healthcare workers' intention to use digital health systems.

The results show that the regression model was statistically significant, with an $R^2$ value of 0.808 and an adjusted $R^2$ of 0.806, indicating that approximately 80 percent of the variation in intention to use was explained by the model. The overall model fit was confirmed by the ANOVA results (F = 425.8, p < 0.001).

Results for specific factors are presented in Figure 1 below. The results show that perceived usefulness, perceived ease of use, job relevance, and subjective norm were all positive and statistically significant factors influencing healthcare workers' intention to use digital health systems. All variables showed positive standardized coefficients and statistically significant p-values, including perceived ease of use (β = 0.358, p <0.001), followed by perceived usefulness (β = 0.284 p = 0.001), job relevance (β = 0.274, p = 0.001) and subjective norms (β = 0.127, p <0.001). However, computer anxiety was negatively and significantly associated with intention to use (β = −0.061, p = 0.001). Computer use was not a significant factor to intention to use digital health systems.

## *Generalized Structural Equation Modelling*

Generalized Structural Equation Modelling was employed to assess the robustness of the findings and to examine the effects of categorical demographic and contextual variables. The GSEM results are reported in Table 6 and corroborate the linear regression results. Perceived usefulness remained a strong and statistically significant predictor of intention to use digital health systems (coefficient = 0.263, p < 0.001), while perceived ease of use also showed a positive and significant association (coefficient = 0.300, p < 0.001).

Computer anxiety continued to exhibit a negative and statistically significant effect on intention to use (coefficient = −0.135, p < 0.001). Among demographic and contextual variables, gender, age, education level, work experience, computer access, and computer use were not statistically significant predictors. However, training on digital health systems showed a statistically significant negative association with intention to use (p = 0.025).Overall, the GSEM results confirm the dominant role of perceived usefulness, perceived ease of use, and computer anxiety in shaping healthcare workers' intention to use digital health systems, while indicating limited direct influence of demographic characteristics.

## Discussion

Health systems in low- and middle-income countries, including Malawi, continue to face persistent challenges related to limited human resources, high patient loads, and constrained access to timely and reliable health data for decision making[14]. Despite growing investments in digital health, healthcare delivery in Malawi remains heavily dependent on paper-based systems, largely due to challenges related to sustainability, interoperability, and coordination of digital health solutions[6]. Against this background, understanding the factors that influence healthcare workers' intention to use digital health systems is critical for informing effective and sustainable digital health integration.

The findings of this study suggest that behavioural and task-related factors play a more central role in shaping intention to use digital health systems than demographic characteristics. Gender differences were found to be statistically insignificant, suggesting that both male and female healthcare workers exhibited similar attitudes toward digital health system adoption. This finding is consistent with recent research, which reported that gender differences in digital health adoption have narrowed substantially due to increased professional exposure to ICT training across health institutions[16].

Similarly, age, education level, and work experience were not significant predictors in the multivariate models, suggesting that adoption intentions are not inherently determined by individual background characteristics. This aligns with recent evidence showing that demographic differences in digital health adoption have narrowed as exposure to information and communication technologies has increased within healthcare systems[7]. While descriptive patterns suggested that younger and early-career professionals exhibited more favourable attitudes towards digital systems, these differences did not translate into statistically significant effects once behavioural perceptions were accounted for. Regional differences in adoption readiness were evident descriptively, with respondents from the Southern Region demonstrating higher intention levels, likely reflecting greater exposure to pilot digital health initiatives and relatively better infrastructure. This finding is consistent with prior studies showing that institutional exposure and system availability enhance readiness and acceptance of digital health systems[19]. It highlights the importance of addressing geographical disparities in infrastructure and implementation when scaling up digital health systems nationally.

Job relevance emerged as one of the strongest predictors of intention to use digital health systems, underscoring the importance of alignment between digital systems and healthcare workers' routine tasks. This finding strongly supports the propositions of the TAM2, which emphasises job relevance as a key determinant of perceived usefulness and behavioural intention[11]. Recent studies in healthcare settings similarly report that systems perceived as directly supporting clinical and administrative responsibilities are more likely to be adopted and used consistently, particularly in high-workload environments[19]. Another study on ICT acceptance in social and healthcare contexts also highlighted that system design tailored to the realities of healthcare work increases both perceived fit and long-term adoption, especially in contexts where staff face heavy workloads and multiple administrative demands[20].

Perceived usefulness was also a strong and consistent predictor of intention to use digital health systems, reinforcing its central role in technology acceptance. This finding is consistent with both the original TAM and its extensions, which identify perceived usefulness as the most influential determinant of behavioural intention[8,11]. Evidence from other low- and middle-income country contexts similarly shows that healthcare workers are more willing to adopt digital systems when these systems demonstrably improve efficiency, effectiveness, and quality of care[13].

Although most respondents reported prior computer use and access to computers, computer use itself was not a significant predictor of intention to use digital health systems. This suggests that basic exposure to computers may no longer be sufficient to drive adoption and that more nuanced factors such as system-specific usability, relevance, and confidence are more critical. Similar findings have been reported in recent digital health studies, which indicate that familiarity with general ICT does not necessarily translate into readiness to adopt complex digital health systems[9].

Training on digital health systems showed a counterintuitive negative association with intention to use in the generalized structural equation model. This may be attributed to poor training quality, reliance on theory-based training, and limited system availability. Reflecting the limitations in quality, relevance, or delivery of existing training programmes, particularly if training is overly theoretical or poorly aligned with users' actual workflows. While prior studies emphasise the importance of training for improving digital literacy and adoption[14,16], poorly designed training may increase frustration rather than confidence. This finding underscores the need for practical, role-specific, and continuous capacity-building approaches among healthcare workers in Malawi.

Computer anxiety emerged as a significant negative predictor of intention to use digital health systems, indicating that psychological barriers remain an important obstacle to adoption. This result is consistent with earlier and recent studies demonstrating that technology-related anxiety reduces behavioural intention and slows digital health adoption[8,11,13]. Addressing computer anxiety through supportive supervision, peer learning, and user-centred system design may therefore be critical for improving adoption readiness.

Social influence, captured through subjective and descriptive norms, also played a significant role in shaping intention to use digital health systems. Expectations from supervisors, facility leadership, and the Ministry of Health, as well as perceptions of peer system use, appear to create normative pressure that encourages adoption. This finding aligns with TAM2, which posits that subjective norms influence perceived usefulness and behavioural intention in organisational settings[11]. Similar effects of social and descriptive norms have been documented in recent studies on digital health and public sector technology adoption[19,21].

Overall, the findings suggest that successful integration of digital health systems in Malawi depends less on demographic characteristics and more on how systems are designed, introduced, and supported. Aligning systems with job roles, clearly demonstrating usefulness, reducing computer anxiety, and leveraging social influence within health facilities are critical for improving adoption readiness. These insights provide important guidance for policymakers and implementers seeking to strengthen digital health systems in Malawi and similar low- and middle-income country contexts. The results will also improve scalability and sustainability of digital health initiatives in Malawi, by prioritizing system

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users and health sector needs, as highlighted in the Malawi Digital Health Strategy, the strong emphasis on scaling up digital health initiatives, including the implementation and expansion of District Health Information System 2 (DHIS2) and Electronic Medical Record (EMR) systems to strengthen health service delivery and data management.

## Conclusion

Low- and middle-income countries continue to face structural and behavioural challenges in the implementation of digital health systems. This study identified job relevance, perceived usefulness, perceived ease of use, and subjective norms, as significant positive determinants of healthcare workers' intention to adopt digital health systems in Malawi. Conversely, computer anxiety was found to have a significant negative effect on adoption intention, indicating that discomfort or fear related to computer use reduces willingness to engage with digital health systems.

The findings demonstrate that behavioural perceptions rather than demographic characteristics are the primary drivers of digital health system adoption among healthcare workers in Malawi. Emphasising that aligning digital health systems with healthcare workers' job roles, ensuring usability, and leveraging social influence within health facilities promotes adoption. They also underscore the need to address psychological barriers to technology use. The Ministry of Health and health facilities should therefore prioritize integrated, practical training and supportive implementation strategies that enhance digital confidence, reduce computer anxiety, and foster sustained use of digital health systems.

## Limitation of the study

This study has limitation that should be considered when interpreting the findings and that provide directions for future research. The cross-sectional design limited the ability to establish causal relationships between the identified factors and intention to use digital health systems; future longitudinal studies could better capture changes in adoption behaviour over time.

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## Ethical approval and consent to participate

Ethical approval for the study was obtained from the Malawi University of Science and Technology Research Ethics Committee (MUSTREC) prior to data collection. The ethical reference number P.04/2025/352.

## Conflicts of Interest

The authors declare no conflict of interest.

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