ORIGINAL RESEARCH ARTICLE

Strategic technology deployment through adoption of a multilevel acceptance management model

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Abstract

In today's data-centric organizational environment, the strategic importance of knowledge as a core resource is increasingly evident. Institutions that effectively harness this resource through technological interventions are better equipped to make informed decisions and deliver high-quality services. Technology plays a vital role in enabling structured data management, facilitating continuous updates, and supporting knowledge organization tools that underpin successful knowledge management (KM) initiatives. These initiatives not only enhance institutional competence but also contribute to improved service delivery and the development of a robust e-governance ecosystem. Despite the clear benefits, many organizations face challenges in the timely and effective adoption of technologies that support KM. To address this, the study proposes a Multilevel Technology Acceptance Management Model that considers the human, technological, and environmental factors influencing technology deployment. The model was validated through a descriptive survey targeting ICT personnel within Kenya's public sector, using regression analysis to assess the relationship between technology acceptance and the identified variables. The results demonstrated statistically significant correlations: human factors ($p < .05$; LL = 0.325; UL = 0.416), technological factors ($p < .05$; LL = 0.259; UL = 0.362), and environmental factors ($p < .05$; LL = 0.282; UL = 0.402). These findings confirm the model's validity and provide sufficient evidence to reject the null hypothesis, affirming its relevance to successful technological intervention implementation. Based on the analysis, the study recommends a three-phase deployment strategy. The first phase should address gaps in human-related factors such as user readiness, training, and change management. This aligns quite well with Nyaga et al., (2025) on the existing risks on technology void of training. The second phase involves creating an enabling environment through infrastructure development, policy support, and organizational alignment. The final phase focuses on the actual deployment of technology, emphasizing usability, scalability, and alignment with institutional goals. This multilevel approach offers a predictive framework for anticipating acceptance challenges and implementing timely mitigation strategies, ultimately enhancing the effectiveness of KM systems and contributing to improved organizational performance.

Keywords: Strategic Technology Deployment, Technology Acceptance, Technology Adoption, Knowledge Management Model, Multilevel Acceptance Management Model.

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1.0 Introduction

The acceptance and increased utilization of technological innovations are critically beneficial to both service providers and users throughout the engagement process (Güçin & Berk, 2015). Amer, Almahri and Saleh (2025) argue that current technology adoption models fail to fully capture human and technology dynamics, particularly in contexts where socio-cultural, psychological and environmental factors significantly influence user behaviour. They emphasise the need for more integrative frameworks that go beyond traditional constructs like perceived usefulness and ease of use., advocating for models that reflect the evolving complexity of digital ecosystems and user expectations. Technology adoption models explain the dynamics of acceptance and the subsequent use of technological interventions. Maier (2007) emphasizes that the success of an information system (IS) cannot be measured directly; instead, it must be assessed through a range of relevant indicators and variables. Since the 1970s, numerous scholars have proposed frameworks to evaluate IS success. Davis et al. (1989), in addressing the persistent challenge of user resistance to technological interventions, contributed to the development of models aimed at explaining computer acceptance and usage behaviour. Schorr (2023) underscores the enduring relevance of the Technology Acceptance Model (TAM) in digitalization research, while also highlighting its conceptual and methodological limitations. He argues that although TAM has been widely adopted across disciplines, its predictive power and adaptability to rapidly evolving digital contexts require critical reassessment and refinement. This research discusses and critiques four prominent technology acceptance models:

i. Theory of Reasoned Action (TRA). Developed by Fishbein & Ajzen (1975), TRA posits that behavioral intention is influenced by an individual's attitude toward the behavior and subjective norms. It assumes rational decision-making based on available information.
ii. Technology Acceptance Model (TAM). Proposed by Davis (1989), TAM builds on TRA and introduces two key constructs: Perceived Usefulness and Perceived Ease of Use, which directly influence users' intention to use a system.
iii. Task Technology Fit Model (TTF). Developed by Goodhue & Thompson (1995), TTF suggests that technology will be used effectively if it fits the tasks users need to perform. It emphasizes alignment between task requirements and technological capabilities.
iv. Unified Theory of Acceptance and Use of Technology (UTAUT). Formulated by Venkatesh et al. (2003), UTAUT integrates elements from eight previous models. It identifies four core determinants of intention and usage: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

The reviewed literature reveals several pertinent empirical gaps that warrant the present study. Numerous studies have employed the Theory of Reasoned Action (TRA) to understand and predict individual behavior in the context of technology and knowledge management (Granick & Marangunić, 2019; Pang et al., 2020; Liang et al., 2021; Oumran et al., 2021). However, a prevailing limitation in these studies is their predominant focus on human

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behavioral aspects, often overlooking the critical roles played by technological and organizational factors in shaping technology acceptance. This narrow scope limits the holistic understanding of adoption dynamics. Future research should therefore expand the scope of TRA-based investigations to include technological and organizational dimensions, particularly within educational and institutional settings where these factors are highly influential.

Similarly, the Technology Acceptance Model (TAM) has been widely used to investigate user adoption of various technologies (Suroso & Retnowardhani, 2017; Gupta et al., 2022; Kelly et al., 2023). Common gaps include the exclusion of external influences like organizational culture, limited consideration of individual differences in technological proficiency, and the inability to fully capture the evolving landscape of AI applications.

The Task Technology Fit (TTF) Model has been applied to assess the alignment between technology and user tasks (Spies et al., 2020; Al-Maatouk et al., 2020; Al-Rahmi et al., 2023; Maue, 2023). However, these studies often rely solely on technological factors, overlooking human and organizational influences. There is also limited exploration of how individual and organizational characteristics affect perceived fit.

Lastly, the Unified Theory of Acceptance and Use of Technology (UTAUT) has been extensively used in KM research (Khanam & Mahfuz, 2018; Gansser & Reich, 2021; Rouidi et al., 2022; Sayginer, 2023). Yet, similar limitations persist, including the exclusion of external factors like organizational culture, insufficient attention to individual technological proficiency, and the need to adapt the model to rapidly evolving technologies such as cloud computing.

1.1 Multilevel technology acceptance management model

Derived from an analysis of existing technology acceptance models and contextualized within the current deployment environment, this study proposes a Multilevel Knowledge Management Acceptance Model. Every system project manager seeks the ability to predict whether a technological deployment will be accepted by its intended users. Davis, Bagozzi, and Warshaw (1989) laid the foundation for this discussion by emphasizing that a model should not only predict acceptance but also diagnose the underlying reasons for potential rejection. This diagnostic capability enables timely corrective actions, thereby increasing the likelihood of successful adoption and maximizing business impact, saving time, resources, and avoiding the deployment of systems that fail to support organizational goals.

Taherdoost (2018) further argues that while numerous models and frameworks exist to explain user adoption or rejection of technological interventions, a single theoretical approach is often insufficient for a comprehensive understanding. This complexity necessitates a model that integrates multiple perspectives and variables relevant to the deployment environment. The model addresses this need by collating constructs from human, technological, and environmental dimensions providing a holistic framework for assessing technology acceptance in knowledge management systems.

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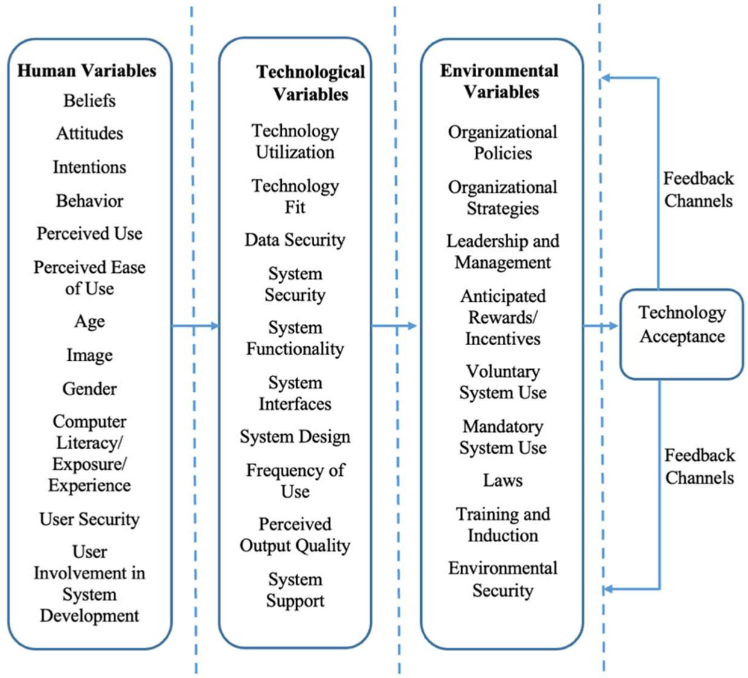

Figure 1. Multilevel knowledge management acceptance model

It is envisioned that the model will enhance understanding and inform the technology deployment process by identifying the key parameters and variables that influence technology acceptance. These variables, synthesized from existing models and contextualized within the current deployment environment, form the foundation of the Multilevel Knowledge Management Acceptance Model, as illustrated in Figure 1 above.

The model depicts three interrelated dimensions which are human, technological, and environmental dimensions that collectively influence the success of technology adoption. Fayad and Paper (2015) observed that adapting variables within the Technology Acceptance Model (TAM) to suit specific application environments addresses its limitations and enhances its robustness and generalizability. This insight supports the rationale for a multilevel approach that integrates diverse constructs relevant to the deployment context.

1.2. Conceptual framework

The conceptual framework guiding this study is grounded in established technology acceptance theories namely; Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Task Technology Fit (TTF) and Unified Theory of Acceptance and use of Technology (UTAUT) contextualized for Kenya's public sector environment.

In this framework, technology acceptance is the primary dependent variable, representing the extent to which ICT personnel in government agencies are willing and able to adopt and utilize

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knowledge management systems. The framework posits that technology acceptance is influenced by three main categories of independent variables namely:

i. Human Factors: these include user attitudes, beliefs, computer literacy, prior experience, perceived usefulness, perceived ease of use, behavioral intentions, and demographic characteristics such as age and gender.
ii. Technological Factors: These encompass system design, functionality, data and system security, user interface, system support, technology fit and perceived output quality.
iii. Environmental Factors: These refer to organizational policies, leadership and management support, training and induction, legal and regulatory frameworks, strategic alignment, incentives and the broader institutional environment.

The framework also recognises that demographic variables such as age, gender, education and experience may act as moderating factors, influencing the strength or direction of these relationships between the independent variables and technology acceptance.

Figure 2 below visually illustrates these relationships, showing how human, technological and environmental factors interact to shape technology acceptance among ICT personnel in Kenyan government agencies. This conceptual framework provides the basis for the study's hypothesis and guides the selection of variables, data collection and analysis.

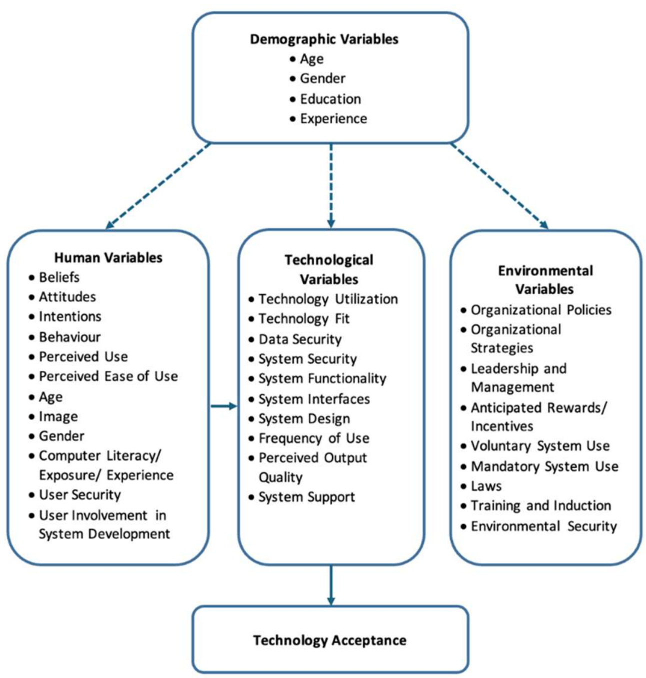

Figure 2. Conceptual framework diagram

2.0 Methodology

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This study adopted a descriptive research design to systematically examine the conditions, characteristics, and behaviours influencing knowledge management acceptance across organizational levels. As Al-Rahmi et al. (2023) note, descriptive designs are ideal for exploring complex phenomena without manipulating variables. This approach enabled a nuanced understanding of the interplay between individual, team, and organizational factors, based on primary survey data collected from selected institutions.

2.1. Scope of the study

This study focussed on the acceptance and deployment of knowledge management technologies within selected government agencies in Kenya. The primary target population comprised of ICT personnel directly involved in the development, deployment and maintenance of public sector information systems. To ensure relevance and diversity, the study purposively selected agencies that are central to Kenya's e-governance and digital transformation agenda. These included but were not limited to Kenya Revenue Authority, ICT Authority, Ministry of ICT, Kenya Forestry Research Institute, National Museums of Kenya, Ministry of Agriculture and other government agencies that have leveraged on systems in service provision.

The selection of these agencies was informed by their unique operational mandates, the critical role they play in national digital infrastructure and their varying levels of technology adoption maturity. By focussing on this cross-section of agencies, the study aimed to capture a comprehensive view of the factors influencing technology acceptance in diverse public sector scenarios and environments. This scope was limited to ICT personnel within these agencies as they are directly responsible for technology adoption decisions, implementation and ongoing system support, thereby highlighting public sector dynamics. Additionally private entities were included based on their strategic role as service providers to government systems, particularly in areas such as software development, infrastructure support and digital transformation consultancy. Their inclusion enriches the study by offering complementary perspectives on technology acceptance from the supply side of public sector digital ecosystems.

2.2. Data collection

A semi-structured questionnaire was administered to ICT personnel in government and private organizations involved in public system development and maintenance. The instrument included both closed-ended questions for quantitative analysis and open-ended questions for qualitative insights. This dual approach allowed for a comprehensive exploration of the contextual factors shaping knowledge management acceptance.

Table 1. Sample data

Variable	Min.	Median	Mean	Max.
Beliefs	2.000	4.500	4.173	5.000
Attitudes	3.000	4.000	4.408	5.000
Intentions	3.000	4.000	4.235	5.000
Behavior	2.000	4.000	3.939	5.000
Perceived Use	2.000	4.000	4.235	5.000

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Variable	Min.	Median	Mean	Max.
Perceived Ease of Use	2.000	5.000	4.459	5.000

2.3. Sample size and sampling technique

A purposive sampling technique was employed to ensure that only ICT professionals with direct experience in technology deployment and knowledge management systems were included in the study. This method was specifically used to target ICT personnel currently employed as ICT officers or system developers within the selected agencies, who are directly involved in implementation, support or management of ICT Systems. This technique ensures relevance and quality of feedback (Maxwell, 2013), aligning with the study's objective to capture informed perspectives on technology acceptance. Yamane's (1967) formula was applied to determine the appropriate sample size. Potential participants were identified through agency staff lists, professional networks and invitations to participate along with the study questionnaire, were distributed via official email channels.

2.4. Response rate

As per the determined sample size, a total of 118 questionnaires were administered by email. Out of this, 98 were duly responded to and returned. This makes a response rate of 83.1% as broken down in Table 2. This approach ensured that the sample was both relevant and representative of the ICT personnel responsible for technology acceptance and deployment decisions within Kenya's public sector.

Table 2. Response rate

	Frequency	Percentage
Response	98	83.5
Non-Response	20	16.5
Total	118	100.0

2.5. Data collection method and instrument

Focused interviews were conducted using a structured questionnaire to gather in-depth data from ICT personnel in government agencies, including those with mandatory systems like KRA. This method uncovered key practices, challenges, and success factors in technology adoption.

2.6. Instrument reliability

The researcher utilized Cohen's Kappa Statistic to test the extent of agreement among survey respondents, also known as interrater reliability. According to Collis and Hussey (2009), rater reliability represents the extent to which the data collected from multiple respondents during research is a true representation of the variables measured. Table 3 shows the reliability test results.

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Table 3. Reliability analysis

	Raw_alpha	Std.alpha	G6(smc)	Average	ase	Mean	sd	Median
Human	0.88	0.89	0.92	0.39	0.018	4.2	0.56	0.4
Technological	0.93	0.93	0.96	0.56	0.011	4.4	0.6	0.55
Environmental	0.77	0.78	0.85	0.29	0.035	4.2	0.49	0.28
Acceptance	0.91	0.92	0.95	0.74	0.014	44	5	0.75

From Table 3, the questionnaire demonstrated notable reliability, with all four variables recording Cronbach's alpha coefficients above the 0.70 threshold originally proposed by Nunnally (1978). Technological variables exhibited the highest reliability at α = 0.93, followed closely by Human variables at α = 0.89. Environmental variables also showed strong internal consistency, with a reliability coefficient of α = 78, confirming the robustness of the instrument across constructs.

These results affirm that the questionnaire is internally consistent and therefore substantially reliable. This is further supported by Cohen's Kappa interpretation framework (Cohen, 1960), which classifies agreement levels as follows: values ≤ 0 indicate no agreement; 0.01–0.20 as slight; 0.21–0.40 as fair; 0.41–0.60 as moderate; 0.61–0.80 as substantial; and 0.81–1.00 as almost perfect agreement. The observed Kappa values for the variables fall within the almost perfect range, reinforcing the reliability of the instrument. In addition, Collis and Hussey (2009) note, interrater reliability is essential for validating survey instruments, especially in complex organizational studies like this one.

2.7. Instrument validity - confirmatory factor analysis

Factor analysis is a multivariate statistical technique used to identify underlying relationships among a large set of observed variables by uncovering latent structures known as factors that explain the patterns of correlations within the data. Its primary goal is to reduce the dimensionality of a dataset while retaining as much meaningful information as possible. This is achieved by grouping variables that are highly correlated into common factors, which represent shared variance among them. In this study, Confirmatory Factor Analysis (CFA) was employed to validate the structure of 32 variables derived from the literature review, grouped under the three primary dimensions of the Multilevel Knowledge Management Acceptance Model: environmental, technological, and human variables. CFA is particularly suitable in this context as it allows researchers to test whether the observed data conform to a hypothesized factor structure based on theoretical foundations or prior empirical findings (Brown, 2015).

The use of CFA was justified both theoretically and methodologically. Each of the three categories; environmental, technological, and human represents a theoretically defined construct domain within the model, consistent with conceptual groupings found in technology acceptance literature, including the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Task-Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; DeLone & McLean, 2003). CFA enabled the

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evaluation of how well the observed indicators aligned with their respective latent constructs within these domains.

For environmental variables, CFA confirmed a structure comprising organizational, regulatory, and motivational factors that influence system adoption within a broader institutional context. These included constructs such as leadership and management, policy frameworks, legal mandates, and system use requirements. Technological variables were validated through constructs related to system design, functionality, security, and user experience which are elements critical to user satisfaction and system acceptance. Human variables were assessed in terms of perceived usefulness, ease of use, behavioural intentions, and demographic moderators, reflecting cognitive and attitudinal dimensions central to user acceptance theories.

2.8. Demographic information

The study evaluated the demographic characteristics of its participants to ensure representativeness across key variables. Data were collected on age bracket, gender, education level, and years of professional experience. These variables were coded in R according to predefined categories. Age was categorized as follows: 1 for 20–25 years, 2 for 26–30 years, 3 for 31–35 years, 4 for 36–40 years, 5 for 41–45 years, and 6 for above 45 years. Gender was coded as 1 for male and 2 for female. Experience was classified into five groups: 1 for 1–5 years, 2 for 6–10 years, 3 for 11–15 years, 4 for 16–20 years, and 5 for above 20 years. Education level was coded as 1 for Diploma, 2 for Bachelor's degree, 3 for Master's degree, and 4 for PhD.

The descriptive statistics presented in Table 4 show that the average age category was 3.18, indicating that most respondents were in the 31–35 year age bracket. The mean gender score of 1.32 suggests a predominance of male participants. The average experience level was 2.46, pointing to most respondents having between 6–10 years of professional experience. In terms of education, the mean score of 2.15 reflects that most participants held a Bachelor's degree. These findings confirm that the study sample was diverse and well-distributed across the demographic spectrum.

Table 4. Demographic information

Age		Gender		Experience		Education	
Min.	1.000	Min.	1.000	Min.	1.000	Min.	1.000
1st	Qu.2.000	1st	Qu.1.000	1st	Qu.1.000	1st	Qu.2.000
Median	3.000	Median	1.000	Median	2.000	Median	2.000
Mean	3.184	Mean	1.316	Mean	2.459	Mean	2.153
3rd	Qu.4.000	3rd	Qu.2.000	3rd	Qu.3.750	3rd	Qu.3.000
Max.	:6.000	Max.	2.000	Max.	5.000	Max.	3.000

As presented in Table 4, the demographic analysis revealed that the average age category of respondents was 3.18, indicating that most participants fell within the 31–35 years age bracket.

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The mean gender score was 1.32, suggesting that most respondents were male. In terms of professional experience, a mean of 2.46 was recorded, implying that most participants had between 6–10 years of working experience in their respective organizations. The average education level was 2.15, indicating that most respondents held a Bachelor's degree. Furthermore, considering the minimum and maximum values, as well as the first and third quartiles across all demographic variables, the results suggest that the study sample was well-distributed and representative of diverse lived experiences in terms of age, gender, experience, and education.

3.0 Results

The results of the study provide empirical evidence on the relationship between technology acceptance and its key predictors: human, technological, and environmental factors. Analysis conducted using RStudio, a powerful integrated development environment for R; a statistical programming language widely used in data analysis, research and modelling, revealed statistically significant associations, confirming that each factor contributes meaningfully to acceptance outcomes. Through diagnostic tests, descriptive summaries, and inferential analysis including correlation and regression the study validated the multilevel model and demonstrated its relevance in guiding effective technology deployment strategies.

3.1. Human variables

The study sought to determine the extent to which respondents perceived various variables as accurately representing human-related characteristics that influence the acceptance of technological interventions. Looking at Ondieki et al., (2024), noting that human factors, user experiences and road aesthetics are important aspects of road planning and design, this inquiry was also grounded in existing research, which suggests that end-user satisfaction is a widely accepted indicator of successful ICT deployment and usability. Respondents provided their views using a 5-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. These human variables encompassed constructs such as perceived usefulness, ease of use, behavioral intention, and demographic moderators—elements that reflect cognitive and attitudinal dimensions central to technology acceptance theories. Table 5 presents the descriptive statistics for the human-related variables, offering insights into how respondents evaluated the relevance and impact of these factors in shaping their acceptance of the technological solution.

Table 5. Descriptive summary for human variables

Variable	Min.	Median	Mean	Max.
Beliefs	2.000	4.500	4.173	5.000
Attitudes	3.000	4.000	4.408	5.000
Intentions	3.000	4.000	4.235	5.000
Behavior	2.000	4.000	3.939	5.000
Perceived Use	2.000	4.000	4.235	5.000
Perceived Ease of Use	2.000	5.000	4.459	5.000
Age	3.000	4.000	4.071	5.000
Image	2.000	4.000	3.969	5.000

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Variable	Min.	Median	Mean	Max.
Gender	1.000	4.000	3.571	5.000
Computer Literacy/ Exposure/ Experience	1.000	5.000	4.531	5.000
User Security	1.000	5.000	4.316	5.000
User Involvement in System Development	1.000	4.000	4.173	5.000

The descriptive results presented in Table 5 indicate that the mean values for human-related variables ranged between 3.571 and 4.531. This suggests that most respondents expressed a high level of agreement that these variables effectively represent human factors influencing the acceptance of technological interventions. Among the most prominent factors, based on their respective mean scores, were: perceived ease of use (4.459), attitudes (4.408), user security (4.316), perceived usefulness (4.235), behavioural intentions (4.235), computer literacy/exposure/experience (4.173), and user involvement in system development (4.173). Additional factors included age (4.071), image (3.969), behaviour (3.939), and gender (3.571). These findings underscore the significance of cognitive, experiential, and demographic dimensions in shaping user acceptance of technology.

3.2. Technological variables

The study aimed to assess the extent to which respondents perceived various variables as accurately representing technology-related characteristics that influence the acceptance of a technological intervention. This investigation was informed by existing research, which highlights that end-user satisfaction is a widely recognized indicator of successful ICT deployment and system usability. Respondents rated their agreement with each item using a 5-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. These technological variables encompassed constructs such as system design, functionality, security, and user experience—elements that are central to user satisfaction and technology acceptance. Table 6 presents the descriptive statistics for the technological variables, offering insights into how respondents evaluated the relevance and impact of these factors in shaping their acceptance of the technological solution.

Table 6. Descriptive summary for technological variables

Variable	Min.	Median	Mean	Max.
Technology Utilization	2.000	4.500	4.337	5.000
Technology Fit	2.000	5.000	4.418	5.000
Data Security	2.000	5.000	4.429	5.000
System Security	2.000	5.000	4.357	5.000
System Functionality	2.000	5.000	4.398	5.000
System Interfaces	2.000	5.000	4.449	5.000
System Design	2.000	5.000	4.367	5.000
Frequency of Use	1.000	4.000	4.235	5.000
Perceived Output Quality	3000	5.000	4.459	5.000
System Support	2.000	5.000	4.469	5.000

The descriptive outcomes presented in Table 6 above reveal mean values ranging from 4.235 to 4.469, indicating that most respondents strongly agreed that the listed variables accurately

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represent technological factors influencing the acceptance of a technological intervention. Among the most prominent factors, based on their respective mean scores, were system support (4.469), perceived output quality (4.459), system interfaces (4.449), data security (4.429), and technology fit (4.418). Other notable factors included system functionality (4.398), system design (4.367), technology utilization (4.337), system security (4.357), and frequency of use (4.235). These findings underscore the importance of technical attributes in shaping user perceptions and acceptance of ICT solutions.

3.3. Environmental variables

The study sought to assess the extent to which respondents perceived various variables as appropriately representing environmental characteristics that influence the acceptance of a technological intervention. This consideration was based on the understanding that external factors whether within or beyond the scope of organizational management can evolve during system deployment and operation, thereby either enhancing or undermining the benefits derived from technology adoption. Respondents rated their agreement using a 5-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. The environmental variables examined included organizational, regulatory, and motivational factors such as leadership and management support, policy frameworks, legal mandates, and system use requirements. Table 7 below presents the descriptive statistics for these environmental variables, offering insights into how respondents evaluated their relevance in shaping technology acceptance within institutional contexts.

Table 7. Descriptive summary for environmental variables

Variable	Min.	Median	Mean	Max.
Organizational Policies	3.00	5.00	4.52	5.00
Organizational Strategies	2.000	5.000	4.378	5.000
Leadership and Management	1.0	5.0	4.5	5.0
Anticipated Rewards/ Incentives	2.000	4.000	4.041	5.000
Voluntary System Use	1.000	4.000	3.847	5.000
Mandatory System Use	1.000	4.000	3.939	5.000
Laws	1.000	5.000	4.296	5.000
Training and Induction	3.000	5.000	4.459	5.000
Environmental Security	2.000	4.000	4.163	5.000

The descriptive outcomes presented in Table 7 show mean values ranging from 3.847 to 4.520, indicating that the majority of respondents strongly agreed that the listed variables accurately represent environmental factors influencing the acceptance of a technological intervention. These factors reflect external influences that may be within or beyond the scope of organizational control and can evolve during system deployment and operation, either enhancing or diminishing the benefits of technology adoption.

Among the most prominent environmental factors, based on their respective mean scores, were organizational policies (4.520), leadership and management (4.500), training and induction (4.459), and organizational strategies (4.378). Other notable factors included laws

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(4.296), environmental security (4.163), anticipated rewards and incentives (4.041), mandatory system use (3.939), and voluntary system use (3.847). These findings highlight the critical role of institutional and contextual elements in shaping user acceptance of technological solutions.

3.4. Diagnostic tests

Before proceeding with regression analysis, the study conducted a series of diagnostic tests to evaluate whether the dataset met the necessary assumptions for reliable statistical modelling. These tests included assessments for outliers, normality, linearity, multicollinearity, and homogeneity of variances. Ensuring that these assumptions hold is critical for the validity and interpretability of regression results, as violations can lead to biased estimates, reduced statistical power, and misleading conclusions.

3.4.1. Test for outliers

According to Collis and Hussey (2009), an outlier is a data point that significantly deviates from the overall pattern of the dataset. Outliers can adversely affect regression models by distorting parameter estimates and reducing the accuracy of predictions. Therefore, identifying and addressing outliers is essential for ensuring the reliability and validity of statistical modelling. In this study, Cook's Distance was employed to detect influential outliers within the dataset. Cook's Distance measures the impact of each observation on the regression coefficients, with higher values indicating greater influence. Observations exceeding the threshold value of 4/n (where *n* is the number of observations) are typically flagged for further review. The results of this analysis are illustrated in Figure 2, which presents the Cook's Distance plot for the dataset.

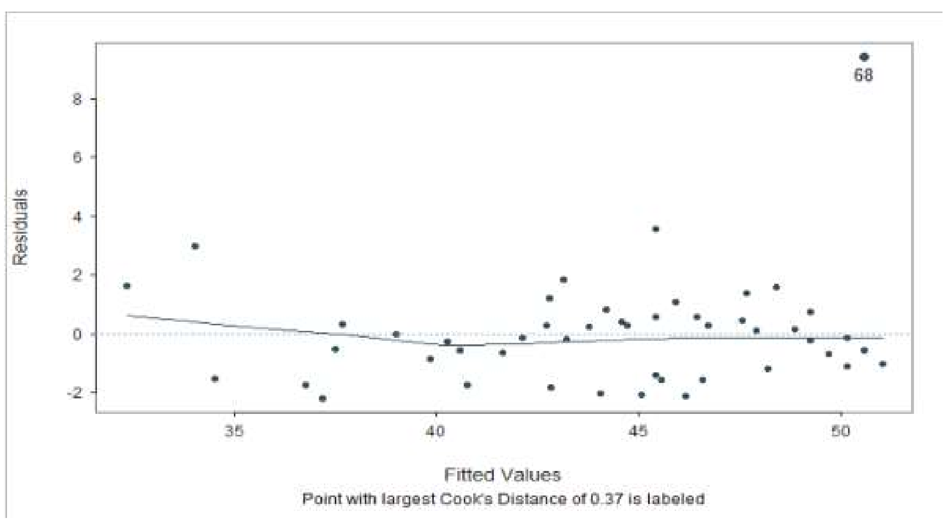

Figure 2. Test for Outliers

As illustrated in Figure 2, only one data point was identified as an outlier, with a Cook's Distance value of 0.37. This value is relatively low and falls below the commonly accepted threshold,

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suggesting minimal influence on the regression model. The remaining data points were well within the acceptable range, indicating no significant distortion in the fitted values. Given the relatively large sample size of 98, the presence of this single outlier was not considered to have a notable negative impact on the model's accuracy. Therefore, with respect to outlier detection, the dataset was deemed suitable for regression analysis.

3.4.2. Test for normality

A fundamental assumption of regression analysis is that the residuals are normally distributed. Violation of this assumption can lead to biased estimates and limit the generalizability of the results. To assess normality in this study, the residuals from the regression model were plotted using a Q-Q (quantile-quantile) plot, as shown in Figure 3. The plot demonstrates that the residuals closely align with the theoretical quantile line, indicating that the data conforms to the normality assumption. Consequently, the dataset was considered suitable for regression analysis with respect to normality.

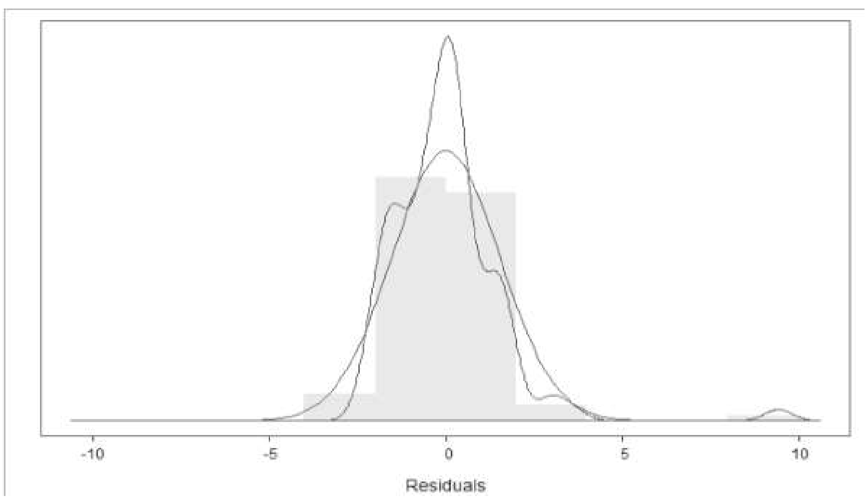

Figure 3. Test for normality

As depicted in Figure 3 above, the residuals from the regression model exhibit a generally normal distribution. The observations form a roughly bell-shaped curve, with a concentration of data points around the centre and fewer points toward the tails. This pattern is evident from both the histogram and the Q-Q plot, where the sample quantiles closely align with the theoretical quantiles. These results indicate that the residuals are approximately normally distributed, thereby satisfying the normality assumption required for regression analysis. Consequently, the data was deemed appropriate for further modelling.

3.4.3. Test for linearity

The linearity assumption in regression analysis posits that there is a straight-line relationship between the dependent and independent variables. In this study, the assumption was assessed through visual inspection of scatter plots to determine whether the distribution of data points

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could be reasonably approximated by a linear trend. As illustrated in Figure 4, the scatter plot depicting the association between human variables and technology acceptance reveals a generally positive linear pattern. This suggests that the linearity assumption holds, and the data is suitable for regression analysis.

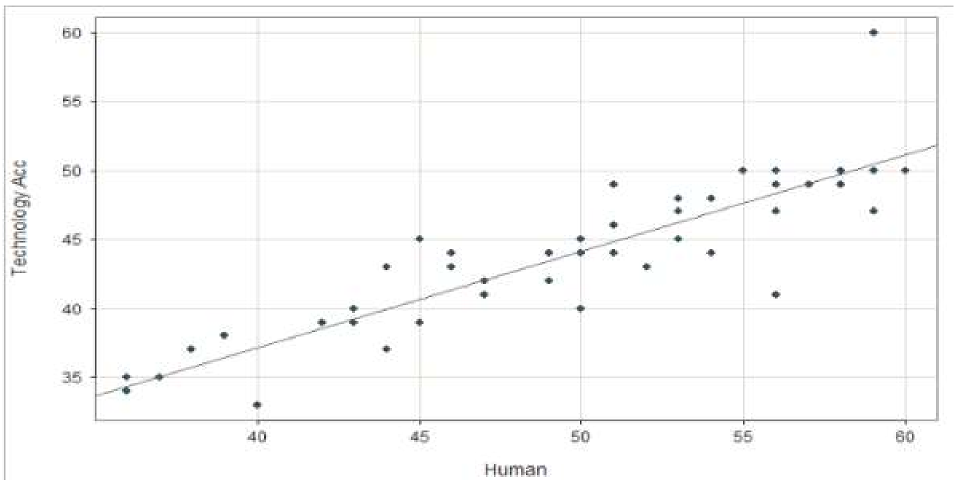

Figure 4. Linearity test result for human variables and technology acceptance

As illustrated in Figure 4, a linear relationship is evident between human variables and technology acceptance. Most data points closely align with the line of best fit, with the exception of a previously identified outlier. This alignment supports the conclusion that the assumption of linearity is satisfied in the association between human variables and technology acceptance. Similarly, a scatterplot was generated to examine the relationship between technological variables and technology acceptance, the results of which are presented in Figure 5.

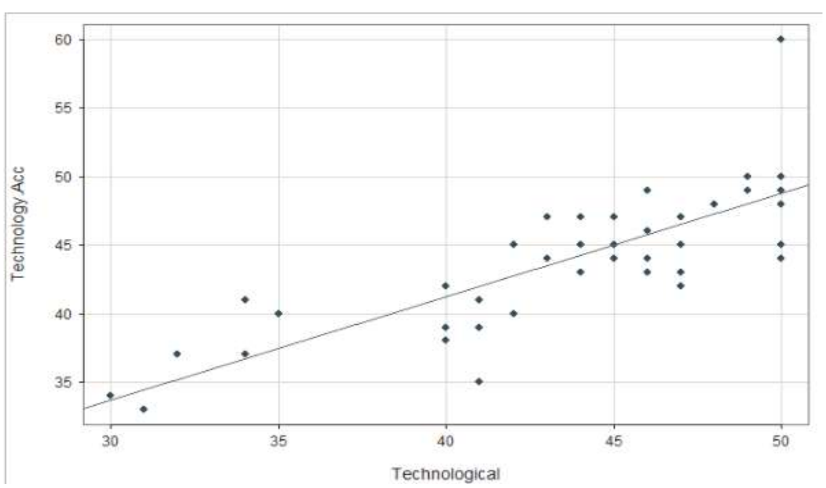

Figure 5. Linearity test result for technological variables and technology acceptance

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As illustrated in Figure 5, a linear relationship is also evident between technological variables and technology acceptance. The majority of data points align closely with the line of best fit, apart from the previously identified outlier. This pattern confirms that the assumption of linearity is satisfied in the association between technological variables and technology acceptance. Additionally, a scatterplot was generated to assess the relationship between environmental variables and technology acceptance, with the results presented in Figure 6.

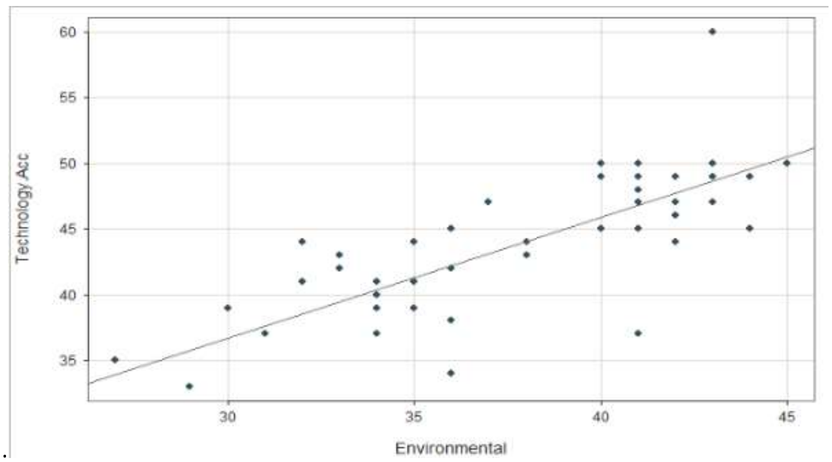

Figure 6. Linearity test result for environmental variables and technology acceptance

As illustrated in Figure 6, a linear relationship is observed between environmental variables and technology acceptance. The majority of data points align closely with the line of best fit, with the exception of the previously identified outlier. This alignment confirms that the assumption of linearity is satisfied in the association between environmental variables and technology acceptance. Having verified the linearity assumption for all three independent variables which are human, technological, and environmental against the dependent variable (technology acceptance). The dataset was deemed suitable for further analysis using regression techniques.

3.4.4. Test for multicollinearity

According to Ghauri and Gronhaug (2010), multicollinearity arises when two or more predictor variables in a regression model exhibit high intercorrelation, typically evidenced by elevated correlation coefficients. This redundancy can undermine the reliability of the model by diminishing the unique contribution of each predictor. A violation of the multicollinearity assumption may result in inflated standard errors, thereby distorting statistical inferences and weakening the explanatory power of the model. To safeguard the robustness of the regression analysis, it was essential to evaluate and address potential multicollinearity among the independent variables. Accordingly, this study conducted a multicollinearity diagnostic, and the results are presented in Table 8 below.

Table 8. Test for multicollinearity

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	Tolerance	VIF
Human	0.448	2.23
Technological	0.442	2.265
Environmental	0.598	1.671

As a rule of thumb, tolerance statistics below 0.2 are indicative of multicollinearity. From the results in Table 8 therefore, all tolerance values were notably above 0.2, hence no problem of multicollinearity in the data. It is therefore inferable from the finding that the 3 independent variables in the study are significantly distinct from each other. Having met this assumption, the data was further considered fit for regression analysis.

3.4.5. Test for homoscedasticity

Regression analysis further assumes that the prediction error in the model does not significantly change over the range of prediction of the model. This is referred to as homoscedasticity and was assessed in this study using the fitted values/residuals plot. It is assumed in this test that the average residual is zero (0) for each level of the predictors in the model. Figure 7 illustrates the finding.

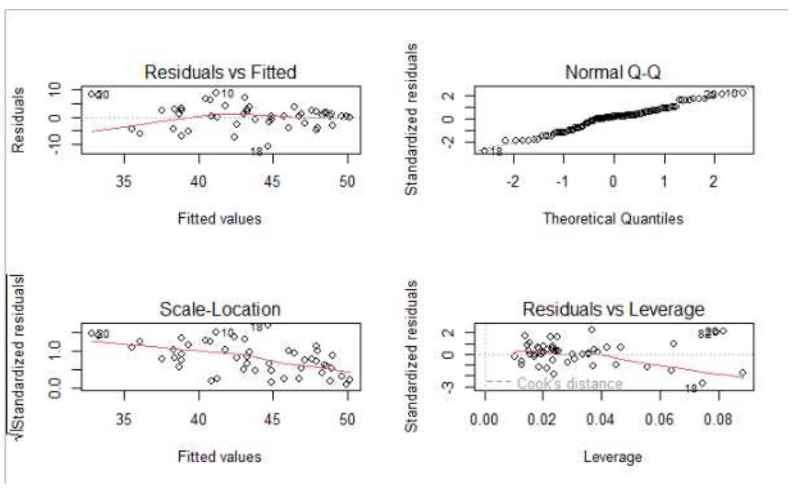

Figure 7. Test for homoscedasticity

As illustrated in Figure 7, the residual and fitted lines are superimposed from the second half of both lines in the residual versus fitted plot. This indicates that the average residual error is about 0 for each level and that there is no heteroskedasticity (violation of homoscedasticity) in the data as the deviation at the beginning of both lines before convergence is not wide. Homoscedasticity can thus be considered present in the data and therefor regression analysis can be conducted.

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3.5 Correlation analysis

To examine the relationship between the independent variables which are Human, Technological, and Environmental factors and the dependent variable, Technology Acceptance, a correlation analysis was conducted. According to the conventional rule of thumb, correlation coefficients below 0.3 indicate a weak relationship, values between 0.3 and 0.5 suggest a moderate relationship, and values above 0.5 reflect a strong relationship. Table 9 below presents the results of this analysis, highlighting the strength and direction of associations among the study variables.

Table 9. Correlation Matrix

	Technology Acceptance	Human	Technological	Environmental
Technology Acceptance	1	0.9	0.87	0.78
Human	0.9	1	0.72	0.58
Technological	0.87	0.72	1	0.59
Environmental	0.78	0.58	0.59	1

As indicated in Table 9, strong correlations were recorded between human variables and technology acceptance variable (0.9); technological variables and technology acceptance variable (0.87); and environmental variables and technology acceptance variable (0.78). A visualization of this matrix is given in Figure 8.

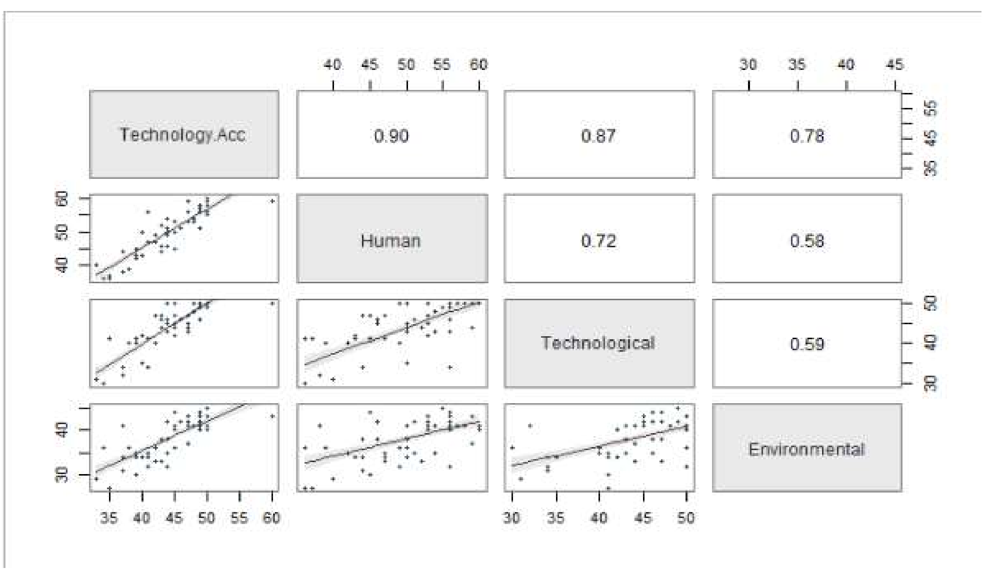

Figure 8. Visualized correlation matrix

The visualized correlation matrix in Figure 8 further illustrates a strong linear association between each independent variables and the dependent variable. While these correlations are significantly high particularly between human variables and technology acceptance variable (0.9), there are significantly distinct each other as indicated by the tolerance statistics.

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3.6 Regression analysis

Having satisfied all the necessary assumptions for regression analysis, the study proceeded to evaluate the extent to which each predictor variable, that is Human, Technological, and Environmental factors contributes to Technology Acceptance, while statistically controlling for the influence of the other variables. This approach enabled the assessment of the individual strength, direction, and significance of each independent variable's effect on the dependent variable, thereby facilitating the testing of the stated hypotheses. The regression analysis produced three key outputs: the Model Fit Summary, the Analysis of Variance (ANOVA), and the Estimated Coefficients Table. These results provide insights into the overall explanatory power of the model, the statistical significance of the regression equation, and the unique contribution of each predictor. Table 10 below presents the model fit summary.

Table 10. Model fit summary

R-squared:	Adjusted R-squared:	PRESS R-squared:
0.963	0.962	0.961
F-statistic:	df:	p-value:
824.508	3 and 94	0

The model fit summary provides insight into the extent to which the three predictor variables; Human, Technological, and Environmental factors collectively explain the variability in Technology Acceptance. As reported in Table 10, the model achieved an adjusted R-squared value of 0.962, indicating that 96.2% of the variance in Technology Acceptance is accounted for by the predictors. This leaves only 3.8% of the variability unexplained, likely attributable to other external factors not captured within the scope of the model.

According to established guidelines, adjusted R-squared values above 0.25 are considered indicative of a large explanatory effect, thereby confirming that the predictors exert a substantial collective influence on Technology Acceptance. Furthermore, the model was found to be statistically significant, with a p-value of 0.000, which is well below the conventional threshold of 0.05 at the 95% confidence level. This result suggests that the data fits the regression model exceptionally well. To further validate the model's significance, an Analysis of Variance (ANOVA) test was conducted. The results of this test are presented in Table 11 below.

Table 11. Analysis of variance

	df	Sum Sq	Mean Sq	F-value	p-value
Human	1	2147.245	2147.245	2078.806	0
Technological	1	274.996	274.996	266.231	0
Environmental	1	132.715	132.715	128.485	0
Model	3	2554.956	851.652	824.508	0
Residuals	94	97.095	1.033		

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Technology Acceptance	97	2652.051	27.341

The ANOVA results presented in Table 11 indicate that the regression model incorporating the three independent variables which are human, technological, and environmental factors is statistically significant. This is evidenced by the p-values of 0.000 for each variable, confirming their strong predictive relationship with the dependent variable, technology acceptance. The model sum of squares (2554.956) compared to the total sum of squares (2652.051) suggests that the model accounts for approximately 96.3% of the variance in technology acceptance, which aligns with the reported R-squared value. The residual sum of squares (97.095) implies that only 3.7% of the variability is attributable to other unexplained or confounding factors. These findings affirm that the model is robust and reliable for drawing conclusions about the influence of human, technological, and environmental variables on technology acceptance. Further details of the regression estimates are provided in Table 12.

Table 12. Estimated Model for Technology Acceptance

	Estimate	Std Err	t-value	p-value	Lower 95%	Upper 95%
(Intercept)	-1.056	0.957	-1.103	0.273	-2.955	0.844
Human	0.37	0.023	16.124	0	0.325	0.416
Technological	0.31	0.026	12.049	0	0.259	0.362
Environmental	0.342	0.03	11.335	0	0.282	0.402

Table 12 presents the estimated effects of each predictor variable on technology acceptance, while statistically controlling for the influence of the other variables. The regression coefficient for human variables is $\beta = 0.37$, indicating that a 1% increase in human-related factors corresponds to a 0.37% increase in technology acceptance, holding technological and environmental factors constant. Similarly, technological variables show a coefficient of $\beta = 0.31$, and environmental variables $\beta = 0.342$, suggesting positive and statistically significant contributions to technology acceptance when controlling for the other predictors.

In terms of predictive strength, human variables emerge as the strongest determinant of technology acceptance, followed by environmental and technological variables, respectively. The standard errors associated with these coefficients are minimal (≤ 0.03), and the t-statistics are notably high (> 10), reinforcing the reliability of the estimates. The p-values for all predictors are $p = 0.000$, well below the 0.05 threshold, confirming statistical significance at the 95% confidence level. Additionally, the lower and upper bounds of the confidence intervals for each coefficient do not cross zero, further validating the robustness of the relationships.

These findings provide compelling evidence to reject the null hypothesis (H_0) that the multilevel knowledge management acceptance model is not significant in predicting successful technological intervention. The study therefore concludes that the model is a critical framework for guiding effective technology adoption and implementation.

4.0 Discussion and theoretical alignment

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The findings of this study reveal a strong consensus among respondents regarding the influence of human, technological, and environmental factors on technology acceptance within the Kenyan public sector. High mean scores across all three dimensions ranging from 3.571 to 4.531 for human factors, 4.235 to 4.469 for technological factors, and 3.847 to 4.52 for environmental factors indicate widespread agreement on their significance. Moreover, all three categories were found to be statistically significant predictors of technology acceptance ($p = .000 < .05$), with confidence intervals confirming the robustness of these relationships.

4.1. Human factors

Human variables emerged as critical determinants of technology acceptance, with key factors including computer literacy, exposure and experience, perceived ease of use, user attitudes, security concerns, perceived usefulness, user intentions, involvement in system development, and age. These findings align with the Technology Acceptance Model (TAM) proposed by Davis et al. (1989), which identifies *perceived usefulness* and *perceived ease of use* as central to user acceptance behavior. Scherer et al. (2018) further affirm that these constructs significantly shape user attitudes toward technological interventions. Additionally, Hwang et al. (2016) highlights that external human factors such as prior experience with computer systems and exposure to automated environments play a vital role in shaping perceptions of usability.

4.2. Technological factors

Technological determinants such as system support, output quality, interface design, data security, technology fit, functionality, utilization, system design, and frequency of use were also found to significantly influence acceptance. These findings resonate with the Task Technology Fit (TTF) Model, which emphasizes the alignment between technology capabilities and task requirements. Lai (2017) underscores that effective technology deployment hinges on its ability to support users in performing their tasks efficiently. Goodhue and Thompson (1995) argue that when a technological solution is well-suited to the task, users perceive it as the optimal tool, enhancing both adoption and performance. Venkatesh et al. (2003) further support this view, noting that both technology utilization and its alignment with task demands are strong predictors of performance outcomes.

4.3. Environmental factors

Environmental variables spanning training and induction, organizational laws and policies, leadership support, strategic alignment, environmental security, and motivational incentives were also perceived as influential. These findings are consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), particularly in relation to facilitating conditions. Alam et al. (2019) and Venkatesh et al. (2003) emphasize the importance of a supportive technical and organizational infrastructure as a key enabler of user acceptance. They argue that successful system deployment must consider environmental readiness to eliminate barriers that may hinder adoption. Alam et al. (2019) also highlight the financial implications of technology adoption such as acquisition, maintenance, and upgrade costs as critical

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considerations. As operational environments evolve, systems must adapt through policy reforms, business model shifts, and technical upgrades to maintain reliability, safety, and service quality.

4.4. Integration with theoretical frameworks

4.4.1. Technology acceptance model (TAM)

The results of this study provide strong empirical support for the Technology Acceptance Model (TAM). Specifically, human-related variables such as perceived ease of use (mean = 4.459) and perceived usefulness (mean = 4.235) recorded high scores, indicating that ICT personnel are more likely to accept and use knowledge management systems when these systems are seen as beneficial and user friendly. Regression analysis further confirmed the significance of human factors, with a standardized coefficient ($\beta = 0.37$, $p < 0.001$), making them the strongest predictors of technology acceptance in this context.

These findings are consistent with Davis et al. (1989), who identified perceived usefulness and ease of use as central to user acceptance. Scherer et al. (2018) affirm that these constructs significantly shape user attitudes, while Hwang et al. (2016) highlights the role of prior experience and exposure in shaping perceptions of usability.

4.4.2. Task-technology fit (TTF)

Technological variables such as system support (mean = 4.469), output quality (mean = 4.459), and technology fit (mean = 4.418) were rated highly by respondents, underscoring the importance of aligning system capabilities with user tasks. The regression coefficient for technological factors was $\beta = 0.31$ ($p < 0.001$), demonstrating a significant positive relationship with technology acceptance. These findings are further supported by Al-Maatouk et al. (2020), who applied the Task-Technology Fit model to evaluate social media platforms in academia, emphasizing that perceived fit significantly influences user satisfaction and continued use.

These results support the Task-Technology Fit (TTF) model by Goodhue and Thompson (1995), which emphasizes that technology adoption is most effective when the system fits the users' work requirements. Lai (2017) further underscores that effective deployment hinges on the technology's ability to support task performance.

4.4.3. Unified theory of acceptance and use of technology (UTAUT)

Environmental factors such as organizational policies (mean = 4.52), leadership support (mean = 4.50), and training and induction (mean = 4.459) were also found to be significant predictors of technology acceptance. The regression coefficient for environmental factors was $\beta = 0.342$ ($p < 0.001$).

These findings are consistent with the UTAUT framework by Venkatesh et al. (2003), which highlights the role of facilitating conditions and organizational support. Alam et al. (2019) adds that financial implications—such as acquisition, maintenance, and upgrade costs—are critical considerations. As operational environments evolve, systems must adapt through policy

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reforms, business model shifts, and technical upgrades to maintain reliability, safety, and service quality.

4.4.4. Theory of reasoned action (TRA)

The study's findings also align with the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen (1975), which posits that behavioural intention is shaped by an individual's attitude toward the behaviour and the influence of subjective norms. In this study, human-related variables such as beliefs (mean = 4.173), attitudes (mean = 4.408), intentions (mean = 4.235), and behavior (mean = 3.939) recorded high scores, indicating that ICT personnel are more likely to accept and use knowledge management systems when they perceive them positively and when there is institutional or peer support for their use.

Regression analysis confirmed the significance of these variables, with human factors yielding the strongest standardized coefficient ($\beta = 0.37$, $p < 0.001$), reinforcing TRA's assertion that behavioural intention is a key predictor of actual behaviour. These results are consistent with prior TRA-based studies (e.g., Granić & Marangunić, 2019; Pang et al., 2020; Liang et al., 2021; Omran et al., 2021), which emphasize the role of cognitive and normative influences in technology adoption. Unlike traditional TRA applications that focus narrowly on human behaviour, this study expands the scope by integrating technological and environmental dimensions, thereby addressing the empirical gaps identified in earlier research.

4.5. Advancement beyond existing models

While TAM, TTF, UTAUT, and TRA each provide valuable perspectives, the Multilevel Knowledge Management Acceptance Model in this study integrates human, technological, and environmental factors, offering a more comprehensive understanding of technology acceptance in the public sector. The model's high explanatory power (adjusted $R^2 = 0.962$) demonstrates its robustness and practical relevance for guiding digital transformation initiatives in Kenyan government agencies.

Recent advancements in technology acceptance research further validate the need for integrative models. For instance, Nilashi & Abumalloh (2025) introduced the i-TAM (Immersive Technology Acceptance Model), which expands TAM by incorporating emotional and social presence dimensions to better capture user engagement in immersive environments. Their work highlights the limitations of traditional models in addressing emerging digital contexts and supports the development of more adaptive frameworks. Al-Rahmi et al. (2023) advocate for integrating communication and task-technology fit theories to enhance digital media adoption, reinforcing the need for multidimensional models like the one in this study.
Similarly, Alwadain et al. (2024) proposed an integrated TTF-UTAUT framework to study electric vehicle adoption, demonstrating that combining task alignment with behavioral constructs yields stronger predictive power. Their findings emphasize the importance of contextual and cross-model integration, reinforcing the value of multilevel approaches in capturing complex adoption dynamics. Gansser and Reich (2021) extended UTAUT2 to include

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AI-specific variables, highlighting the need for evolving models that accommodate emerging technologies, an approach echoed in the multilevel framework.

Compared to these recent models, the Multilevel Knowledge Management Acceptance Model distinguishes itself through its explicit emphasis on organizational context, public sector dynamics, and cross-dimensional interdependencies. This comprehensive perspective ensures a more accurate representation of the factors influencing technology adoption, making it a significant contribution to the evolving landscape of digital transformation research.

5. Summary of key findings and conclusion – objective based

5.1 Objective 1: To examine the influence of human factors on technology acceptance among ICT personnel in Kenyan government agencies.

The study found that human-related variables including perceived ease of use (mean = 4.459), user attitudes (mean = 4.408), and computer literacy/experience (mean = 4.531) were the strongest predictors of technology acceptance. Regression analysis confirmed that human factors had the highest standardized coefficient ($\beta = 0.37$, $p < 0.001$), highlighting the critical role of user competence, attitudes, and behavioural intentions in successful adoption of knowledge management systems. These findings align with the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA), which emphasize the importance of perceived usefulness, ease of use, and behavioural intention in shaping user acceptance.

5.2 Objective 2: To assess the impact of technological factors on technology acceptance.

Technological factors such as system support (mean = 4.469), output quality (mean = 4.459), and technology fit (mean = 4.418) were also significant predictors of acceptance. The regression coefficient for technological factors was $\beta = 0.31$ ($p < 0.001$), indicating that the alignment of system capabilities with user needs and robust technical features are essential for fostering acceptance. These results reflect the principles of the Task-Technology Fit (TTF) model, which posits that technology must align with user tasks and expectations to be effectively adopted.

5.3 Objective 3: To evaluate the effect of environmental factors on technology acceptance.

Environmental variables including organizational policies (mean = 4.52), leadership and management support (mean = 4.50), and training and induction (mean = 4.459) were found to be significant, with a regression coefficient of $\beta = 0.342$ ($p < 0.001$). These findings underscore the importance of supportive institutional environments, clear policies, and ongoing capacity building in promoting technology adoption. This aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes facilitating conditions and organizational readiness as key enablers of user acceptance.

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5.4 Objective 4: To validate the proposed multilevel knowledge management acceptance model.

The model demonstrated high explanatory power, with an adjusted R^2 of 0.962, indicating that human, technological, and environmental factors collectively explained 96.2% of the variance in technology acceptance. All predictors were statistically significant, and the model's robustness was confirmed through diagnostic tests and ANOVA. Compared to existing models such as Gupta et al.'s Integrative Technology Adoption Framework and Rouidi et al. (2022). Extended UTAUT, the model distinguishes itself by explicitly integrating multilevel dynamics and organizational context, offering a more holistic and context-sensitive framework for public sector technology deployment.

5.5 Conclusion

The study concludes that a multilevel approach integrating human, technological, and environmental dimensions provides a comprehensive and predictive framework for understanding and enhancing technology acceptance in Kenya's public sector. These findings offer actionable insights for policymakers and practitioners seeking to implement digital transformation initiatives, emphasizing the need to address user readiness, strengthen technical infrastructure, and foster enabling organizational environments. This aligns with recent work by Lee, Ramasamy, and Subbarao (2025), who emphasize that successful technology adoption requires a holistic strategy that incorporates psychosocial readiness, organizational support, and contextual adaptation of acceptance models.

6.0 Recommendations

6.1. Enhance user readiness and capacity building

Government agencies should invest in continuous training and change management programs to improve ICT personnel's computer literacy, perceived ease of use, and positive attitudes toward new technologies. These human factors validated as the strongest predictors of technology acceptance, align with the Technology Acceptance Model (TAM) and Theory of Reasoned Action (TRA), which emphasize user competence and behavioural intention. Structured capacity-building initiatives will foster confidence and reduce resistance to new systems.

6.2. Strengthen technical infrastructure and system support

Agencies should prioritize the development and deployment of robust, user-friendly, and secure knowledge management systems. Emphasis should be placed on system support, output quality, and technology fit to ensure that technological solutions align with user needs and organizational tasks. These recommendations are grounded in the Task-Technology Fit (TTF) model, which highlights the importance of aligning system capabilities with task requirements to enhance performance and adoption.

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6.3. Foster supportive organizational environments

Leadership and management should actively support technology adoption by establishing clear policies, providing incentives, and ensuring strategic alignment. Regular training and induction programs should be institutionalized to build a culture of innovation and adaptability. These environmental factors are consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), which identifies facilitating conditions as critical enablers of user acceptance.

6.4. Integrate multilevel acceptance considerations in policy and practice

Policy frameworks should explicitly incorporate human, technological, and environmental factors when planning and implementing digital transformation initiatives. This multilevel approach, validated by the study's high explanatory power (adjusted $R^2 = 0.962$) will help anticipate and mitigate acceptance challenges, leading to more effective technology deployment. As Lee, Ramasamy, and Subbarao (2025) emphasize, holistic strategies that integrate psychosocial readiness and organizational support are essential for successful adoption.

7.0 Further research

Future studies should explore additional moderating variables such as organizational culture, external environmental factors, and demographic diversity. Longitudinal designs could assess technology acceptance over time, while comparative studies across sectors or regions may reveal contextual nuances. Expanding the model's application will enhance its generalizability and relevance to broader digital transformation efforts.

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