DEMYSTIFYING TECHNOLOGY ADOPTION THROUGH IMPLEMENTATION OF A MULTILEVEL TECHNOLOGY ACCEPTANCE MANAGEMENT MODEL

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ABSTRACT

Successful data driven decision making in any organization is anchored on the tenets of knowledge as a strategic resource. Successful adoption of a technological intervention to harness this pivotal resource is key. Institutions leverage on technology for prudent data management to drive knowledge management (KM) initiatives towards quality service delivery. These initiatives provide the overall strategy for managing data resources through making available knowledge organization tools and techniques while enabling regular updates. Some of the benefits derived from positive deployment of a technological intervention are competency enhancement through gained knowledge, raised quality of service and promotion of healthy development of an e-commerce operating environment. Timely, focused and successful adoption of technological interventions through which knowledge management initiatives are deployed remains a key challenge to many organizations. This paper proposes a multilevel technology acceptance management model. The proposed model takes into account human, technological and organizational variables, which exist in a deployment environment. To validate the model, a descriptive survey was conducted sampling ICT personnel in the Kenyan Public Sector. A regression analysis framework was adopted to determine the statistical relationship between the dependent (technology acceptance) and independent (human, technological and environmental) variables. Results indicate that technology acceptance in the Kenyan public sector is significantly predicted by human variables ($p=.00<.05$; $LL=0.325$; $UL=0.416$); technological variables ($p=.00<.05$; $LL=0.259$; $UL=0.362$) and environmental variables ($p=.00<.05$; $LL=0.282$; $UL=0.402$). Based on the findings, it is deduced that the proposed multilevel technology acceptance model is validated. The findings also provide sufficient evidence to reject the null hypothesis that the multilevel knowledge management acceptance model is insignificant to successful technological intervention implementation. The study therefore concludes that the multilevel knowledge management acceptance model is of crucial importance to successful technological intervention implementation. The study recommends a multilevel technology deployment process at 3 key levels. The first level ought to address any gaps in the identified human-related factors, while the second level in the deployment process involves providing an enabling environment for adoption of the intervention. The third level entails the actual deployment of the technological intervention with a focus on key features of the technologies involved. This model will be vital in driving early technology acceptance prediction and timely deployment of mitigation measures to deploy technological interventions successfully.

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KEYWORDS

Technology Acceptance, Technology Adoption, Knowledge, Management Model, Multilevel, Technology Model

1. INTRODUCTION

The acceptance and increased utilization of technological innovations are crucially beneficial for both the service provider and user during the whole process of engagement (Gucin & Berk, 2015). A technology adoption model explains the acceptance and consequent use of a technological intervention. Maier (2007) notes that success of any information system (IS) cannot be measured directly, but has to be assessed using a number of measures which are relevant for success. He notes that since the 70s, many authors have developed approaches to assess the success of an IS through several proposed variables, indicators and measures. As Davis et al. (1989) continue to ponder on the challenge of users rejecting technological interventions, this concern lead to the study of several models that aim to explain computer acceptance and usage behaviour. This research discusses and critique four technology acceptance models as mentioned below.

i. Theory of Reasoned Action (TRA)
ii. Technology Acceptance Model (TAM
iii. Task Technology Fit Model (TTF)
iv. Unified Theory of Acceptance and Use of Technology (UTAUT)

The reviewed literature brought to the fore a number of pertinent empirical gaps that warrant the present study in an effort to address them. Several studies have utilized TRA to understand and predict the factors influencing individual behavior in the field of technology and knowledge management (Granic & Marangunic, 2019; Pang et al., 2020; Liang et al., 2021; Oumran et al., 2021). An overriding gap in the extant studies however is the focus on the human aspects in the context of technology acceptance, overlooking the technological and organizational aspects. Future research could explore technology acceptance with the educational settings, with the inclusion of both technological and organizational aspects.

Similarly, numerous studies within the realm of technology and knowledge management have employed TAM to investigate user acceptance and adoption of various technologies (Suroso &Retnowardhani, 2017; Chooprayoon & Fung, 2020; Gupta et al., 2022; Kelly et al., 2023). Common empirical gaps however includes the exclusion of external factors that may influence technology acceptance, such as organizational culture; the lack of consideration for individual differences in technological proficiency; as well as the fast-paced evolution of AI, and the studies not being able to capture the full spectrum of AI applications.

Further, the TTF Model has been applied in technology and knowledge management studies to assess how well a technology aligns with the tasks and needs of its users (Spies et al., 2020; Al-Maatouk et al., 2020; Al-Rahmi et al., 2023; Mauye, 2023). However, common limitations in the reviewed literature include the reliance on technological factors in assessing how well a technology aligns with the tasks and needs of its users, overlooking the human and organizational factors; as well as the limited exploration of individual differences and organizational characteristics in influencing perceived fit.

The UTAUT model has also been a widely employed model in technology and knowledge management studies (Khanam & Mahfuz, 2018; Gansser & Reich, 2021; Rouidi et al., 2022;

Sayginer, 2023). A common limitation is the exclusion of external factors that may influence technology acceptance, such as organizational culture; the limited exploration of individual differences in technological proficiency; as well as the potential for the rapid evolution of cloud technologies, suggesting the need for ongoing research to adapt the UTAUT model to the changing landscape of knowledge management systems.

1.1. Proposed Multilevel Technology Acceptance Management Model

Derived from analyzing the choice models while mirroring this knowledge to the current deployment environment, the researcher proposes a multilevel knowledge management acceptance model as illustrated. Every system project manager would love to be able to predict whether the technological deployment will be acceptable to the envisioned users. Davis, Bagozzi and Warshaw (1989) laid a foundation to this discussion by recommending that a model should also be in a position to diagnose the base reasons why a proposed system may not be fully acceptable to the users, providing an opportunity for corrective action to be taken, increasing acceptability of a technological intervention. This will increase business impact, saving time and resources that would otherwise go to waste deploying and supporting a system that is unproductive and does not support the business goals. Taherdoost (2018) explains that although a number of models and frameworks have been developed, explaining user adoption or rejection of new technological interventions, more than one theoretical approach is necessary for a wholesome understanding of the issues involved. This creates a cumbersome process and consequently, need for a model that when applied, encompasses most of the possible variables that exists in a deployment environment is key. The apparent need for further research into models that provide an ever-richer understanding of technology adoption through collating constructs that relate to each other with representation from the human, technological and environment perspectives are considered. The proposed model aims to bring more clarity to technological deployment process through assessing key parameters that are found within the deployment environment. It groups the key variables into three main categories:

i. Human variables
ii. Technological variables
iii. Environmental variables

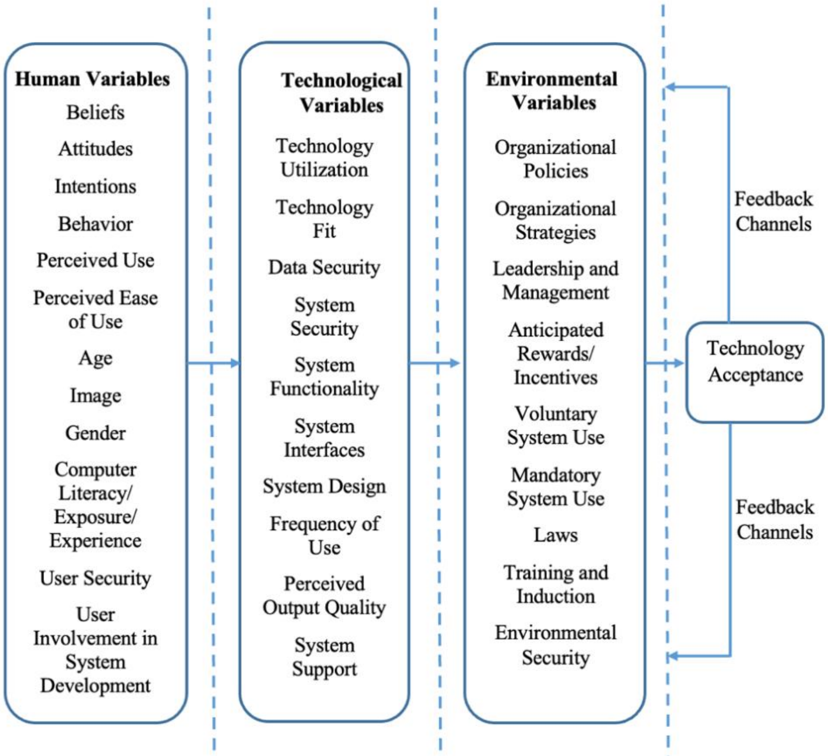

Figure 1. Proposed Multilevel Knowledge Management Acceptance Model

It is envisioned that this will bring understanding and inform the technology deployment process on the parameters and key variables that need to be focused on for technology acceptance. The proposed variables with their corresponding factors are synthesized into a multilevel knowledge management acceptance model that forms a foundation for the present research, as illustrated in Figure 1. The illustrated model below depicts the three multilevel dimensions towards technology acceptance. It has been observed that the application of variables to TAM that are dependent to the application environment address its limitations and potentially confirm its robustness and generalizability, Fayad & Paper (2015).

2. RESEARCH DESIGN

The research design employed in this study was the descriptive research design. This choice is justified by the need to systematically investigate and understand the existing conditions, characteristics, and behaviours related to knowledge management acceptance across multiple organizational levels. As per Al-Rahmi et al. (2023), a descriptive design allows for the comprehensive exploration of the phenomena associated with knowledge management acceptance models, capturing the intricacies of knowledge management acceptance without intervening or manipulating variables. Through primary survey data, the study aimed to provide an in-depth portrayal of the current state of knowledge management acceptance within the selected organizations, shedding light on the multilevel factors influencing this acceptance. This approach facilitated a nuanced understanding of the complex interplay between individual, team, and organizational factors without introducing external interventions, ensuring the study's focus on describing and interpreting the existing phenomena surrounding multilevel knowledge management acceptance models.

2.1. Data Collection

A targeted survey using semi-structured questionnaires was administered to ICT personnel in government institutions and private organizations involved in the development and maintenance of public systems. The survey questionnaire included both closed- and open-ended questions. Quantitative data was obtained from the closed parts of the questionnaire, while the open-ended parts yielded qualitative data which allowed for a rich exploration of the intricate nuances and contextual factors influencing the acceptance of knowledge management practices within the specified roles**.** Table 1 below presents the sample data, with which the study sought to establish the extent to which respondents perceive various variables as appropriately representing human-related characteristics that determine the level of acceptance of a technological intervention.

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
Perceived Ease of Use	2.000	5.000	4.459	5.000

2.2. Response Rate

As per the determined sample size, a total of 118 questionnaires were administered by email. Out of this, 98 were dully responded to and returned. This makes a response rate of 83.1% as broken down in Table 2.

Table 2. Response Rate

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

2.3. 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.

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 was notably reliability, with all 4 variables recording reliability coefficients above the 0.7 threshold originally proposed by Nunnally (1978). Technological variables had the highest reliability coefficient at 0.93, trailed by Environmental variables at 0.91. Human variables also recorded a reliability coefficient, followed by environmental variables. The questionnaire used in the study can therefore be considered internally consistent and therefore substantially reliable. This is further in line with Cohen (1960) who suggested the Kappa result be interpreted as follows: values ≤ 0 as indicating no agreement and 0.01–0.20 as none to 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.

2.4. Demographic Information

The study participants were assessed for their demographic profiles. In this regard, the information that was sought comprised of the respondents' age bracket, gender, education level and experience. This would give an indication of the study's representativeness across the demographic spectrum. To this end, demographic information was coded into r based on the various response categories. For age, these included 1 = 20-25 Years, 2 = 26-30 Years, 3 = 31-35 Years, 4 = 36-40, Years, 5 = 41-45 Years and 6 = Above 45 Years. For gender, 1 = Male and 2 = Female; while for 1 = 1-5 Years, 2 = 6-10 Years, 3 = 11-15 Years, 4 = 16-20 Years and 5 = Above 20 Years. For level of Education, 1 = Diploma, 2 = Bachelors, 3 = Masters and 4 = PhD. Outcomes of the study in this regard are as shown in Table 4.

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, a mean of 3.18 shows that most respondents were within the 31-35 Years age bracket; while a mean of 1.32 in gender implies that a majority of respondents were of the male gender. A mean of 2.46 was further recorded in respondents' experience, implying that a majority of respondents had working experience in their respective organizations and were of the age between 26-30 Years. Lastly, a mean of 2.15 was recorded in education which is of the implication that a majority of respondents had a bachelors degree. Also considering the 1st and 3rd quarters as well as minimum values and maximum values, the results imply that the study findings are representative of various lived experiences by age, gender, experience and education.

3. RESULTS

The three main variables explored in the study were analyzed for their manifestations among the institutions reached in the survey. In this regard, respondents were asked to indicate their respective levels of agreement with statements pertinent to various human, technological and environmental-related factors as apt determinants of the level of acceptance of a technological intervention.

3.1. Human Variables

The study sought to establish the extent to which respondents perceive various variables as appropriately representing human-related characteristics that determine the level of acceptance of a technological intervention. This was against the backdrop of research showing that the level of end-user satisfaction with an information technology intervention has widely been accepted as an indicator of ICT deployment and usability success. Responses were given on a 5-Point Likert scale, where 1= strongly disagree, 2= strongly disagree, 3 = neutral, 4= strongly disagree, 5 = strongly disagree. Table 5 presents the descriptive results.

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
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 from Table 5 show mean values ranging between 3.571 and 4.531, implying that a majority of respondents were highly in agreement that the foregoing variables represent human factors that determine the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these factors include computer literacy/ exposure/ experience (4.173); perceived ease of use (4.459); attitudes (4.408); user security (4.316); perceived use (4.235); intentions (4.235); user involvement in system development (4.173); age (4.071); image (3.969); behavior (3.939); and gender (3.571).

3.2. Technological Variables

The study sought to determine the extent to which respondents perceive various variables as rightly representing technology-related characteristics that determine the level of acceptance of a technological intervention. This was against the backdrop of research showing that the level of end-user satisfaction with an information technology intervention has widely been accepted as an indicator of ICT deployment and usability success. Responses were also given on a 5-Point Likert scale, where 1= strongly disagree, 2= strongly disagree, 3 = neutral, 4= strongly disagree, 5 = strongly disagree. Table 4.5.2 presents the descriptive results.

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

Variable	Min.	Median	Mean	Max.
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 from Table 6 indicate mean values ranging between 4.235 and 4.469, which is of the implication that a majority of respondents were highly in agreement that the foregoing variables represent technological factors determining the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these factors include system support (4.469); perceived output quality (4.459); system interfaces (4.449); data security (4.429); technology fit (4.418); system functionality (4.398); system design (4.367); technology utilization (4.337); system security (4.357); and frequency of use (4.235).

3.3. Environmental Variables

The study sought to determine the extent to which respondents perceive various variables as aptly representing environmental characteristics that determine the level of acceptance of a technological intervention. This was in consideration of other external factors that may be within or beyond the scope of management and may change during deployment and operations, influencing the technology adopted either positively or may negate the gains derived through its adoption. Responses were also given on a 5-Point Likert scale, where 1= strongly disagree, 2= strongly disagree, 3 = neutral, 4= strongly disagree, 5 = strongly disagree. Table 7 presents the descriptive results.

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 from Table 7 indicate mean values ranging between 3.847 and 4.52, meaning that a majority of respondents were highly in agreement that the foregoing variables represent environmental factors determining the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these environmental factors include training and induction (4.459); organizational policies (4.52); leadership and management (4.5); organizational strategies (4.378); laws (4.296); environmental security (4.163); anticipated rewards/ incentives (4.041); mandatory system use (3.939); and voluntary system use (3.847).

3.4. Diagnostic Tests

Prior to conducting regression analysis, the study analyzed the various assumptions to determine whether the data was fit for regression. These included tests for outliers, normality, linearity, multi-collinearity as well as homogeneity of variances.

3.5. Test for Outliers

Collis and Hussey (2009) define an outlier as a data point which detaches itself from the rest of the data within the model. Outliers have been found to have a negative effect on the regression equation often resulting in inaccurate results. Their detection is therefore important for effective modelling and for accuracy of results. In this study, Cooks Distance was used to check for outliers, results of which are projected in Figure 2.

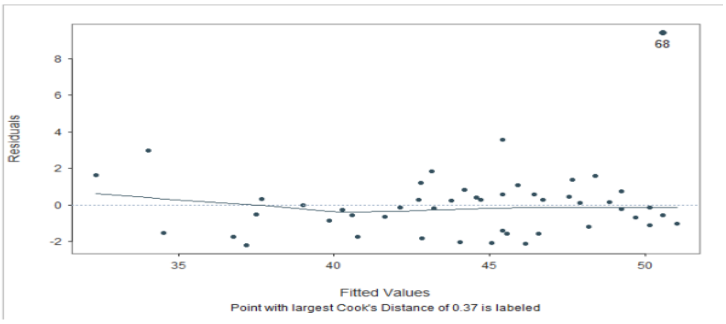

Figure 2. Test for Outliers

As observed in Figure 2, only one (1) data point was found to be an outlier, with a Cook's Distance of 0.37 which is relatively low. The rest of the residual datapoints were within range. Considering the relatively large sample size of 98, this outlier was deemed not to have any notable negative impact on the fitted values. As regards outliers therefore, the data was considered fit for regression analysis.

3.6. Test for Normality

A key assumption of regression analysis is that data are normally distributed. A violation of normal distribution in regression analysis results in inaccurate outcomes from skewed data, which cannot be generalized as being reflective of the study population. To check for normal distribution in the data, all residuals and errors in the model were plotted and the results are as illustrated in Figure 3 below.

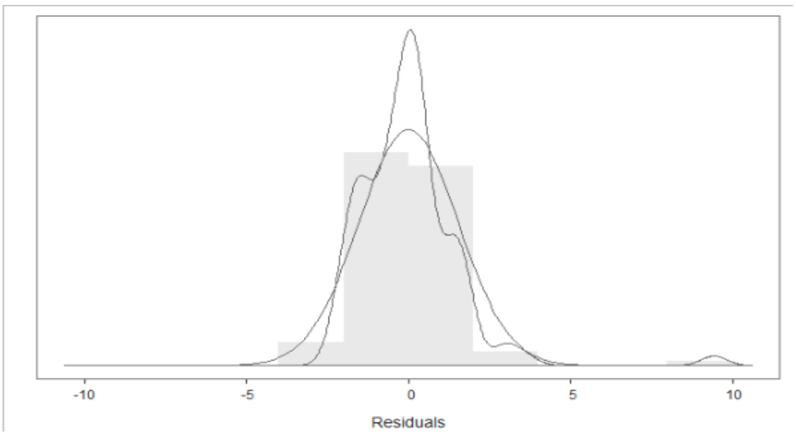

Figure 3. Test for Normality

As depicted in Figure 3, a generally normal distribution curve was observed in the model's residuals and errors. The observations are roughly bell-shaped with more observations in the middle of the distribution and fewer on the tails, based on both the histogram and the line curve. This implies that there was normal distribution in the data and therefore the same was fit for regression analysis.

3.7. Test for Linearity

Linearity assumption in regression analysis presumes that there is a linear association between the dependent and independent variables. In this study, linearity assumption was tested through a visual assessment of scatter plots to see if the distribution of data points could be described with a straight line. Figure 4 illustrates the scatterplot for the association between human variables (independent variable) and technology acceptance (dependent variable).

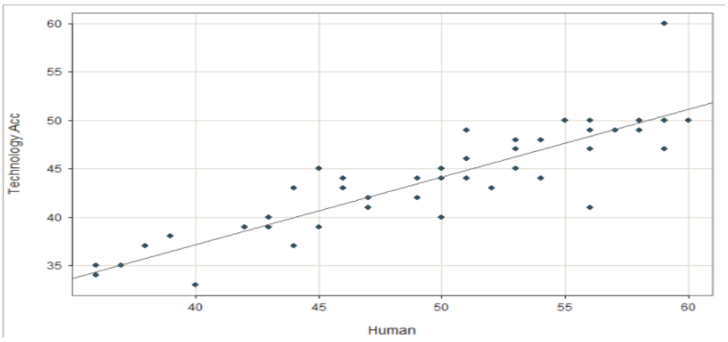

Figure 4. Linearity Test Result for Human Variables and Technology Acceptance

As Figure 4 displays, a linear association is observed between human variables and technology acceptance, with a majority of the datapoints aligning along the line of best fit save for the outlier earlier detected. It can therefore be deduced that linearity assumption was met in the association between human variables and technology acceptance. A scatterplot was also produced for the association between technological variables and technology acceptance, results of which are displayed in Figure 5.

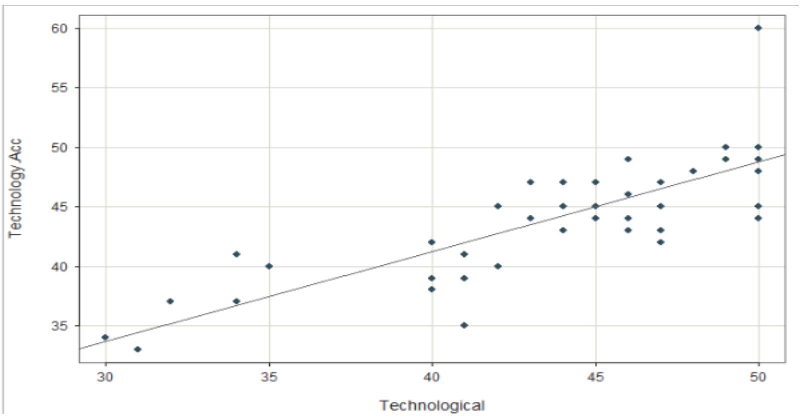

Figure 5. Linearity Test Result for Technological Variables and Technology Acceptance

As Figure 5 displays, a linear association is observed between technological variables and technology acceptance, with a majority of the datapoints aligning along the line of best fit except for the outlier earlier detected. It can therefore be deduced that linearity assumption was met in the association between technological variables and technology acceptance. A scatterplot was also produced for the association between environmental variables and technology acceptance, results of which are displayed in Figure 6.

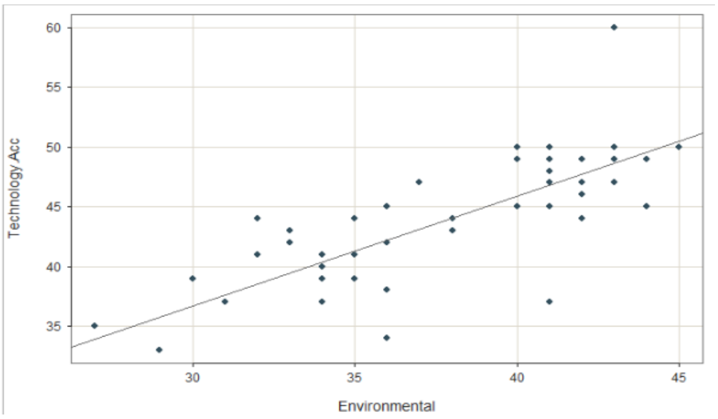

Figure 6. Linearity Test Result for Environmental Variables and Technology Acceptance

As Figure 6 displays, a linear association is observed between environmental variables and technology acceptance, with a majority of the datapoints aligning along the line of best fit except for the outlier earlier detected. It can therefore be deduced that linearity assumption was met in the association between environmental variables and technology acceptance. Having met the assumptions of linearity for all 3 independent variables against the dependent variable, the data was further deemed fit for regression analysis.

3.8. Test for Multicollinearity

According to Ghauri and Gronhaug (2010), multicollinearity occurs when 2 or more determinant variables in the model overlap significantly with each other as indicated by the correlation coefficients. A violation of this assumption results in inaccurate outcomes owing to the use of redundant or indistinct variables. It is therefore imperative to identify and correct the problem of multicollinearity. As such, multicollinearity assumption was tested in this study and results are presented in Table 8.

Table 8. Test for Multicollinearity

	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.

3.9. 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.

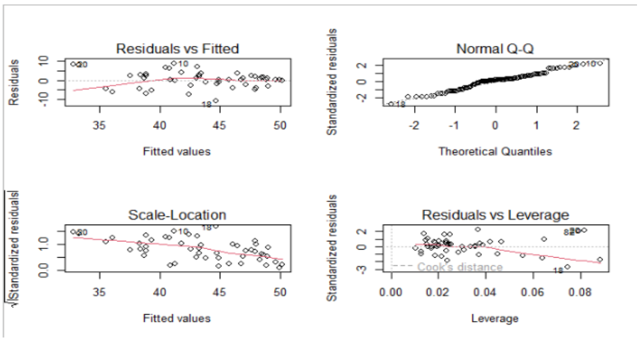

Figure 7. Test for Homoscedasticity

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.

3.10. Correlation Analysis

A correlation analysis was conducted in order to determine the strength of the linear association between the independent variables (Human, Technological and Environmental variables) and the dependent variable (Technology Acceptance). The rule of thumb is that correlation values (r) of 0.3 and below indicate a weak correlation; values between 0.3 and 0.5 indicate a medium correlation; while values above 0.5 indicate a strong correlation. Table 9 presents the results.

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.

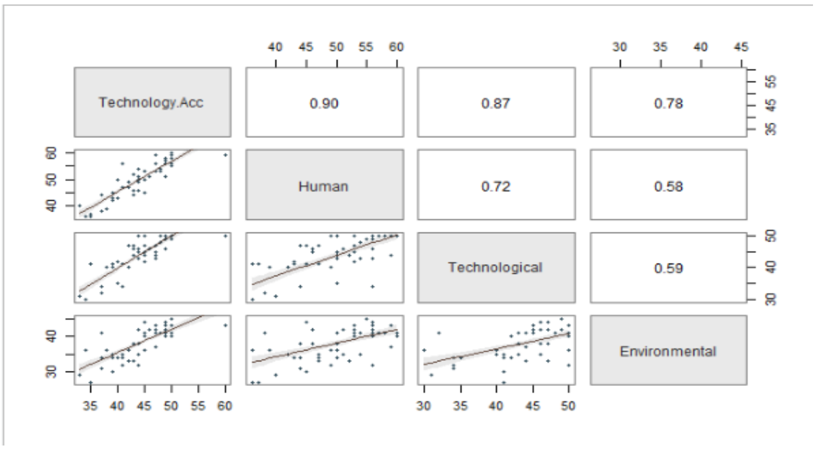

Figure 8. Visualized Correlation Matrix

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.

3.11. Regression Analysis

Having met all assumptions, the study proceeded to conduct the regression analysis with a view to determine the extent to which each predictor variable predicts technology acceptance while statistically controlling for the other variables. With this, regression analysis would show the individual strength, direction and significance of each independent variable on the dependent variable keeping other factors constant, hence testing the stated hypothesis. Three outcomes were produced, including the model fit summary, Analysis of Variance (ANOVA) and the estimated model table. Table 10 shows 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 shows the amount of variability in technology acceptance, accounted for by thee 3 predictors that is human, technological and environmental variables. The rule of thumb is that R squared values between 0.01 and 0.09 indicate a large explanatory effect; while values between 0.09 and 0.25 indicate a medium explanatory effect; and values above 0.25 indicate a large explanatory effect. From the results in Table 4.9, an adjusted R squared value of 0.962 was recorded, which was converted into a percentage by multiplying by 100. This indicates that human, technological and environmental variables collectively account for 96.2% of the variability in technological acceptance while only 3.8% of the variability is left unexplained and accountable to other variables not included in this model. This implies that human, technological and environmental variables have a collectively large explanatory effect on the variability in technological acceptance. This was also statistically significant with a P value of 0.0, which is less than the 0.05 threshold at 95% confidence level, indicating that the data fits the model significantly well. An ANOVA test was also produced from the regression analysis and the results are shown in Table 11.

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		
Technology Acceptance	97	2652.051	27.341		

ANOVA results in Table 11 indicate that the regression model fitting the four variables is statistically significant as indicated by the P-values of 0.0 for all three independent variables against the dependent variable. The total sum of squares is 2652.051 vis a vis the model sum of squares at 2554.956 further implying that with human, technological and environmental variables accouting for 96.3% of the variability in technology acceptance which is consistent with the R squared value. The residual sum of squares is 97.095 which means that only 3.7% of the variability in the model can be ascribed to other confounding factors not fitted in the model. This further indicates that the model fitting human, technological and environmental variables as predictors of technology acceptance is statistically significant and can be relied upon to draw conclusions. Table 12 shows the regression outcomes for the estimated model.

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

Results in Table 12 shows the estimated effect of each predictor variable on technology acceptance while statistically controlling for the other predictor variables. The regression coefficient of 0.37 in human variables means that for every 1% increase in human variables, there is a correlated 0.37% increase in technology acceptance, controlling for both technological and environmental variables. Meanwhile, for every 1% increase in technological variables, there is a 0.31% increase in technology acceptance, controlling for both human and environmental variables. Further, for every 1% increase in environmental variables, there is a 0.342% increase in technology acceptance, controlling for both technological and environmental variables. In order of strength therefore, human variables (β=0.37) are the strongest predictors of technological acceptance, followed by environmental variables (β=0.342) then technological variables (β=0.31). The standard errors for these regression coefficients are very small ($\leq$.03) and the t-statistics are very large (>10). The *p*-values reflect these small errors and large t-statistics.

The P values, at 95% confidence level, as well as lower and upper bound limits (both not crossing 0 in the integer line) associated with each relationship further show significance meaning that for all variables, there is almost zero probability that these effects are due to chance. This indicates that human variables are a significant predictor of technology acceptance (p=.00<.05; LL=0.325; UL=0.416); technological variables are a significant predictor of technology acceptance (p=.00<.05; LL=0.259; UL=0.362); and that, environmental variables are a significant predictor of technology acceptance (p=.00<.05; LL=0.282; UL=0.402). The findings provide sufficient evidence to reject the null hypothesis that the multilevel knowledge management acceptance model is insignificant to successful technological intervention implementation (H_0). The study thus conclude that the multilevel knowledge management acceptance model is of crucial importance to successful technological intervention implementation.

4. DISCUSSION

A majority of respondents were found to highly agree that the stated variables represent human factors that determine the level of acceptance of a technological intervention. This was indicated by high mean values ranging between 3.571 and 4.531. It was also found that human variables are a significant predictor of technology acceptance (p=.00<.05; LL=0.325; UL=0.416). It can be inferred from the finding, that a majority of staff in the Kenyan public sector perceive human factors as highly determining their level of acceptance of a technological intervention in government institutions. Key among these factors include computer literacy/ exposure/ experience; the technological intervention's perceived ease of use; attitudes; user security; perceived use; intentions; user involvement in system development; and age. This is expected, as humans are the primary stakeholders in any technological intervention in a workplace setting and therefore the degree to which the intervention is accepted is squarely dependent on human factors. Employees are likely to take up a technology if they deem it useful in their daily execution of task and that they have the proficiency to adopt it.

High mean values were further recorded between 4.235 and 4.469 in technological factors, indicating that a majority of respondents highly agree that the stated variables represent technological factors determining the level of technological acceptance. Technological variables were also found to be significant predictors of technology acceptance (p=.00<.05; LL=0.259; UL=0.362). It is deducible from the finding, that that a majority of staff in the Kenyan public sector perceive technological factors as greatly determining their level of acceptance of a technological intervention in government institutions. Key among these factors include system support, perceived output quality, system interfaces, data security, technology fit, system functionality, system design, technology utilization, system security and frequency of use. By their very nature, technological variables are expectedly central and critical to the effective uptake of a technological innovation. With adequate system support for instance, potential users are motivated to take up a product with the assurance that should anything go wrong, support will be promptly provided. This will also encourage continuous usage and recommendation of the technological intervention to others.

A majority of respondents were found to highly agree that the stated variables represent environmental factors that determine the level of acceptance of a technological intervention. This was indicated by high mean values ranging between 3.847 and 4.52. Environmental variables were further to be a significant predictor of technology acceptance (p=.00<.05; LL=0.282; UL=0.402). It can be inferred from the finding, that environmental factors are a notable determinant in the acceptance of technological innovation. These span attributes across operational, managerial and policy levels of an organizational workplace context. Specific variables in this regard incorporate parameters such as the level of training and induction among staff; organizational laws and policies requiring or inhibiting adoption of technology as whether mandatory or voluntary use; leadership and managerial support; organizational strategies necessitating or otherwise, the uptake; environmental security requiring acceptance; as well as such motivators as anticipated rewards/ incentives.

The proposed model's revelation that human, technological and environmental variables significantly predict technology acceptance aligns with recent literature that propose models emphasizing the multifaceted nature of user behavior in technology adoption. Scholars such as Gupta et al. (2022) and Rouidi et al. (2022) have put forth models that underscore the importance of individual-level factors in technology acceptance. These models, inspired by the foundations laid by UTAUT and TAM, acknowledge the centrality of human variables, but often stop short of fully integrating technological and organizational elements into their frameworks. In contrast, the proposed model takes a leap forward by encompassing not only individual-level predictors but also considering the symbiotic relationships between human, technological, and organizational variables within the deployment environment. This represents a more recent and comprehensive approach to understanding the dynamics of technology acceptance.

Compared to recent studies proposing models such as Gupta et al.'s (2022) Integrative Technology Adoption Framework and Rouidi et al.'s (2022) Extended Unified Theory of Acceptance and Use of Technology, the proposed model distinguishes itself by its explicit emphasis on multilevel variables. While these recent models acknowledge the interconnectedness of certain factors, they often do not delve deeply into the specific dynamics within the deployment environment. The proposed model, on the other hand, goes beyond the conventional focus on individual attitudes and technological features by integrating organizational aspects. Recent studies, although valuable in advancing our understanding of technology acceptance, may not fully capture the complexity of real-world deployment scenarios, making the proposed model's multilevel perspective a unique contribution in the landscape of more recent technology acceptance models.

In evaluating the performance of the proposed model against recent models, it becomes apparent that the proposed model stands out for its holistic approach. While recent studies contribute by refining and expanding upon existing models, the proposed model's innovation lies in its recognition that technology acceptance is not a singularly determined phenomenon. Models proposed by Gupta et al. (2022) and Rouidi et al. (2022) have made strides in acknowledging contextual influences, but the proposed model advances further by explicitly integrating the multilevel dynamics present in deployment environments. By doing so, it offers a more nuanced and comprehensive understanding of the complex interplay between human, technological, and organizational factors, making it a promising advancement in recent technology acceptance research. The proposed model's incorporation of a broader set of variables ensures a more accurate representation of the factors influencing technology acceptance, setting it apart from the narrower perspectives found in some recent studies.

The finding is in concurrence with TAM as advanced by Davis et al. (1989), opining that perceived usefulness and perceived ease of use are pivotal acceptance behavior variables towards technology acceptance. In agreement, Scherer et al. (2018) intimate that perceived ease of use and perceived usefulness revolve around the TAM model and are key in determining user attitude towards onboarding a technological intervention. Similarly, Hwang et al. (2016) observes that external human parameters like experience working on computer systems, years spent on automated systems, exposure to technology among others greatly influence the user's perspective on how easy or difficult it is to use the system.

The finding is consistent with the Task Technology Fit Model (TTF) which as cited by Lai (2017) underscores the degree to which a technology deployment assists an individual in performing his portfolio of tasks, pointing to system functionality, frequency of use, technology utilization and technology fit. Also in agreement, Goodhue and Thompson (1995) observe that when a technological intervention offers features that are just right for the purposed task, the user will feel that this is the technological tool of choice, hence the fit. This perceived sense of a tool that eases the task load through features that break down the task into doable subtasks while simplifying the whole process, optimally leading to better utilization and performance. The level of technological fit is a strong predictor of better performance. Similarly, Venkatesh et. al. (2003) posit that utilization of a technology and the leveraged technology should be a good fit to the task deployed as predictors of performance. Its underlying mantra is that technologies must be utilized and fit the task they support to have a performance impact. It provides clear relationship on the technological, user tasks and utilization variables as they relate towards progressive or retrogressive performance.

The finding is in agreement with the UTAUT model, in which Alam et al. (2019) and Venkatesh et. al. (2003) describe facilitating conditions like existence of needed technical infrastructure in an organization to provide a good base for the new technology as a key indicator towards user acceptance. Venkatesh et. al. (2003) observe that during development and deployment of any system, it is prudent to consider the environmental and technological system use needs for removing any obstacles that may cause technology rejection. Deployment of a good technological intervention in an environment that is not ready or responsive to its adoption and optimum use is already a recipe for failure. Similarly, Alam et al. (2019) aver that the costs associated with acquisition, use and maintenance of technological interventions is a pivotal factor to consider when considering any system. Growing needs and changes in the operational environment call for changes in the structure of any system. This may be new laws governing the use of the technology, changed business model or just upgrades for increased dependability, safety and quality of service call for periodic maintenance and updates. Users therefore are quite aware of these needs and their corresponding financial effect on the overall budget for maintenance.

4.1. Summary of Key Findings

The study sought to establish the extent to which respondents perceive various variables as aptly representing human-related characteristics that determine the level of acceptance of a technological intervention. To achieve this objective, pertinent questionnaire items were advanced to which respondents were required to indicate their levels of affirmation to respective human related characteristics as determining their individual levels of acceptance of a technological intervention. The descriptive results on human-related characteristics show mean values ranging between 3.571 and 4.531, implying that a majority of respondents were highly in agreement that the foregoing variables represent human factors that determine the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these factors include computer literacy/ exposure/ experience (4.173); perceived ease of use (4.459); attitudes (4.408); user security (4.316); perceived use (4.235); intentions (4.235); user involvement in system development (4.173); age (4.071); image (3.969); behavior (3.939); and gender (3.571).

The study also sought to determine the extent to which respondents perceive various variables as aptly representing technology-related characteristics that determine the level of acceptance of a technological intervention. To achieve this objective, pertinent questionnaire items were advanced to which respondents were required to indicate their levels of affirmation to respective technology related characteristics as determining their individual levels of acceptance of a technological intervention. The descriptive results on technology-related characteristics mean values ranging between 4.235 and 4.469, which is of the implication that a majority of respondents were highly in agreement that the foregoing variables represent technological factors determining the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these factors include system support (4.469); perceived output quality (4.459); system interfaces (4.449); data security (4.429); technology fit (4.418); system functionality (4.398); system design (4.367); technology utilization (4.337); system security (4.357); and frequency of use (4.235).

The study sought to determine the extent to which respondents perceive various variables as aptly representing environmental characteristics that determine the level of acceptance of a technological intervention. To achieve this objective, pertinent questionnaire items were advanced to which respondents were required to indicate their levels of affirmation to respective environment related characteristics as determining their individual levels of acceptance of a technological intervention. The descriptive results on environmental characteristics indicate mean values ranging between 3.847 and 4.52, meaning that a majority of respondents were highly in agreement that the foregoing variables represent environmental factors determining the level of acceptance of a technological intervention. Based on the respective levels of agreement, key among these environmental factors include training and induction (4.459); organizational policies (4.52); leadership and management (4.5); organizational strategies (4.378); laws (4.296); environmental security (4.163); anticipated rewards/ incentives (4.041); mandatory system use (3.939); and voluntary system use (3.847).

The study then proceeded to conduct the regression analysis with a view to determine the extent to which each predictor variable predicts technology acceptance while statistically controlling for the other variables. It was found that human variables are a significant predictor of technology acceptance ($p=.00<.05$; LL=0.325; UL=0.416); technological variables are a significant predictor of technology acceptance ($p=.00<.05$; LL=0.259; UL=0.362); and that, environmental variables are a significant predictor of technology acceptance ($p=.00<.05$; LL=0.282; UL=0.402). The findings provide sufficient evidence to reject the null hypothesis that the multilevel knowledge management acceptance model is insignificant to successful technological intervention implementation (H_0).

5. CONCLUSION

Based on the foregoing findings, it is deduced that the proposed multilevel technology acceptance model is validated. The study concludes that technological acceptance for service delivery in the Kenyan public sector is significantly predicted by 3 main variables, that is human variables, technological variables and environmental variables. In order of strength, human variables are the strongest predictors of technological acceptance, followed by environmental variables then technological variables.

Human variables are the strongest predictors of technology acceptance in the Kenyan public sector. The extent to which staff thereof will buy into a technological innovation is mainly hinged on their exposure and proficiency in the use of the technological software and hardware involved; the extent to which they perceive the said technology as easy to use and potentially useful; their attitude towards the intervention; their perceived security in the adoption; as well as their involvement at important levels in the intervention processes.

Environmental variables are the second strongest predictors of technological acceptance in the Kenyan public sector. The extent to which staff in government institutions in the country effectively adopt a technological innovation is dependent on key contextual operational, managerial and policy attributes. Institutions with a committed and supportive leadership are particularly more likely to record success in the adoption of a technological innovation, compared to the contrary. Equally, institutions with such enabling policies and laws as making the technological intervention mandatory along with training and reward practices have higher chances of achieving a successful intervention compared to those with laws and policies with a voluntary approach and that do not train or reward their staff for adoption.

Technological variables are also a significant predictor of technology acceptance in government institutions. Preceded with both human and environmental variables, the extent to which staff in government institutions in the country effectively adopt a technological innovation is dependent on various technological variables. Successful technological intervention in the public sector presupposes that the technology's functionality fits the daily work and task routine; that system support be provided; that the system features a user-friendly interface; that the system's output is of good quality; and that it addresses data protection and user security.

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