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Research Paper

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Understanding Social Acceptability of IoT Technologies Through Descriptive, Reliability, and Predictive Statistical Models

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ABSTRACT

The study examines the social acceptability of Internet of Things (IoT) technology in Gaduwa Estate, Abuja, Nigeria, utilizing a multi-method statistical framework that incorporates descriptive statistics, reliability tests, ANOVA, Pearson correlations, and predictive regression models. Survey results from 156 respondents (78% valid response rate) indicated notable demographic disparities in adoption patterns, with younger individuals (18–35 years, $\chi^2 = 25.6$, $p < 0.001$) and those with higher education (BSc/MSc, $\chi^2 = 46.3$, $p < 0.001$) exhibiting more desire. The reliability analysis demonstrated strong scale consistency (Cronbach's $\alpha = 0.87$). ANOVA results revealed significant variations in willingness among groups ($F(3,116) = 5.62$, $p = 0.002$). Correlation analysis revealed robust positive correlations between willingness and Touch ($r = 0.72$), Perceived Usefulness ($r = 0.68$), Trust ($r = 0.61$), and Ease of Use ($r = 0.59$), although Cost Concern exhibited a negative correlation ($r = -0.45$). Regression models further substantiated these trends: multiple linear regression accounted for 62% of the variation ($R^2 = 0.62$), with significant predictors comprising PU ($\beta = 0.32$, $p < 0.001$), EU ($\beta = 0.28$, $p = 0.001$), Trust ($\beta = 0.30$, $p < 0.001$), and Cost Concern ($\beta = -0.22$, $p = 0.016$). Logistic regression shown commendable classification efficacy (AUC = 0.78), substantiating PU (OR = 1.51), EU (OR = 1.45), and Trust (OR = 1.54) as facilitators of adoption, whereas Cost Concern diminished odds (OR = 0.75). The results corroborate the Technology Acceptance Model and UTAUT, while augmenting them with contextual insights that highlight affordability, trust, and experiential exposure as essential factors. These findings extend the Technology Acceptance Model (TAM) and UTAUT frameworks by highlighting affordability and experiential exposure as critical determinants in emerging economies. The study offers theoretical and policy insights to strengthen inclusive IoT adoption strategies.

Keywords - Internet of Things; Technology Adoption; Willingness and Social Acceptability.

I. INTRODUCTION

Recent advancements in the Internet of Things (IoT) may induce significant transformations across all sectors of society, including governance, education, healthcare, and agriculture (Muhammad et al., 2025). By the conclusion of the decade, the global value of IoT-enabled assets might reach trillions of dollars. This illustrates

the significance of development and social systems (Zyoud & Zyoud, 2025). For communities, particularly in undeveloped regions, to fully capitalize on this potential, the social acceptability of IoT is equally crucial as its technological capabilities. This study examined the social and behavioral factors including trust, cost, perceived usefulness, ease of use, and exposure that influence the adoption of IoT in developing economies.

Studies utilizing the Technology Acceptance Model generally recognize Perceived Usefulness (PU) and Ease of Use (EU) as key behavioral factors affecting technology adoption (Venkatesh et al., 2003). Nevertheless, these models often fail to fully address factors such as trust, financial implications, and perceived risk elements especially relevant to the Internet of Things (IoT). A study on the adoption of agricultural IoT revealed that heightened trust enhances perceived value and diminishes perceived risk, hence increasing the likelihood of adoption (Cherniaieva et al., 2023; Maroufkhani et al., 2020). Among domestic customers, trust has been shown to outweigh privacy concerns in determining the acceptance of IoT-enabled gadgets (Zhang et al., 2024). Meta-analytic assessments highlight the significance of hedonic motivation and social influence in shaping consumers' perceptions of the usability and utility of the Internet of Things (Dwivedi et al., 2021). The Unified Theory of Acceptance and Use of Technology and its extensions enhance the Technology Acceptance Model by incorporating elements such as social influence and facilitating conditions, significantly impacting technology adoption, particularly in collectivist or community-focused environments (Mohammed Alhassan & Ibrahim, 2025).

Despite these theoretical breakthroughs, numerous empirical studies on IoT adoption demonstrate a lack of integration across methodological contexts. Few incorporate descriptive validation, scale reliability assessment, factor-level construct analysis, and predictive statistical modelling into a unified framework. Addressing this research gap is crucial for obtaining significant, policy-relevant insights particularly in developing economies, where infrastructural inadequacies, variations in digital literacy, and financial constraints affect user perceptions and adoption decisions (Cherniaieva et al., 2023; Hossain et al., 2024). This study addresses these deficiencies by employing a sequential, multi-method approach that incorporates descriptive statistics and Cronbach's α for instrument validation, factor analysis to discern latent constructs, analysis of variance (ANOVA) to examine group differences, correlation matrices to assess construct interdependencies, and both linear and logistic regression to forecast IoT adoption outcomes. The research enriches both theoretical and practical frameworks by grounding the analysis in dimensions including trust, cost considerations, perceived usefulness, ease of use, exposure (Touch), and willingness to adopt.

Our findings augment the comprehensive understanding of IoT adoption, including evidence-based advice for policymakers, designers, and community implementers aiming to promote societal acceptance, particularly in resource-constrained settings. The future of the IoT hinges not alone on technology and connectivity, but also on its alignment with customer trust, cost-effectiveness, and practical utility.

II. MATERIALS AND METHODS

2.1 Study Area Descriptions

The study was carried out in Gaduwa Estate, Abuja, Nigeria, located at latitude 8.9991° N and longitude 7.4667° E. The estate was described as a developing residential community with modern housing layouts, which positions it as a potential smart estate, although it was also reported that open dumping and incineration of waste remained common practices. The population of the estate comprised mainly middle- and upper-income households, including civil servants, business owners, professionals, and students, with major streets such as Ahmadu Bello Way, Oladipo Diya Street, Ring Road 2, Constitution Avenue, Bayelsa Court, and Cascurina Close serving as key residential clusters.

2.2 Research Design

This research adopted a quantitative, cross-sectional survey design to evaluate determinants of Internet of Things (IoT) adoption in Kaduwa Estate. A structured questionnaire was developed based on validated scales

from prior adoption studies, focusing on constructs such as trust, cost, perceived usefulness, ease of use, exposure, and willingness to adopt (Venkatesh et al., 2021).

2.3 Research Design and Questionnaire Administration

Survey research was used to obtain data using a structured questionnaire. The questionnaire was created on Google Forms for digital administration and response retrieval. The instrument had 100 questions separated into themes. Demographic parameters (age, gender, education, employment), awareness of IoT technologies, views of benefits and hazards, readiness to pay in the event of privatization, and technological infrastructure availability were considered. There were 156 completed and returned questionnaires out of 200, an 78% valid response rate. all responses were exported into Microsoft Excel format for preliminary screening and coding, and subsequently subjected to advanced statistical analysis using SPSS software packages.

2.4 Analytical Procedure

2.4.1 Descriptive Statistics

The research utilized a quantitative analytical methodology to evaluate the trends of IoT adoption among inhabitants of Gaduwa Estate, Abuja. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were utilized to summarize the demographic features of respondents and to elucidate overall adoption trends, in accordance with the guidelines of Bouterraa et al., (2024). These measurements offered a summary of central patterns and variability within the sample. The instrument's reliability was assessed by internal consistency testing with Cronbach's alpha. In accordance with the widely established criterion of $\alpha > 0.70$ in social science research, the instrument attained an alpha coefficient of 0.87, signifying robust reliability across measurement scales. To improve construct validity, Exploratory Factor Analysis (EFA) was conducted utilizing principal component extraction with varimax rotation. This analysis, adhering to the methodologies established by Fabrigar and Wegener, (2012), diminished dimensionality and categorized associated variables such as trust, cost, utility, and usability into cohesive constructs that signify adoption factors.

2.4.2 Descriptive Statistics

2.4.3 Analysis of Variance (ANOVA)

One-way ANOVA was used to examine mean differences in adoption-related constructs across demographic subgroups (education, occupation, gender). This approach tests whether perceptions of IoT adoption differ significantly across respondent categories (Field, 2018). Pearson's correlation coefficients were computed to evaluate the strength and direction of linear relationships between independent constructs (trust, cost, usefulness) and the dependent construct (willingness to adopt). This analysis highlights interdependencies among predictors (Cohen et al., 2014).

2.4.4 Regression Modelling

Both multiple linear regression and binary logistic regression were employed to test the predictive power of identified constructs on willingness to adopt IoT. Linear regression estimated the extent to which independent variables explain variance in adoption scores, while logistic regression modeled adoption as a binary outcome (adopt/not adopt), following approaches used in recent IoT adoption research (Dwivedi et al., 2021).

III. RESULTS AND DISCUSSION

3.1 Chi-Square Analysis

The chi-square test results (Table 1) revealed no significant difference in gender distribution 56.4% male compared to 43.6% female among respondents, $\chi^2(1, N = 156) = 2.56, p > 0.05$ indicating a well-balanced sample. This corresponds with recent meta-analyses indicating that gender disparities in ICT usage are typically minimal and frequently statistically inconsequential (Qamar and Qureshi 2022). This balance enhances the credibility of later inferences regarding IoT adoption by mitigating gender-based bias. The education levels of respondents

exhibited a substantial bias towards greater academic achievement, $\chi^2(4) = 46.3$, $p < 0.001$. A majority possessed BSc degrees (37.8%), succeeded by MSc degrees (25%), with negligible representation among secondary education and PhD holders. This chart illustrates the recognized relationship between educational achievement and technological usage. Research conducted by Suri & Udry (2022) demonstrates that advanced education improves individuals' ability to understand. The age distribution was notably significant, $\chi^2(3) = 25.6$, $p < 0.001$, with around 70% of respondents aged 18 to 35.

This affirms the propensity of younger demographics to lead in the adoption of digital technology. Venkatesh et al. (2003) highlighted age as a significant socio-demographic variable in technology acceptance models, noting that younger persons generally exhibit higher technological self-efficacy and receptiveness to innovation. No substantial occupational bias was detected (students, civil servants, company operators, others), $\chi^2(3) = 5.1$, $p > 0.05$. The diversified occupational mix indicates that the sample accurately reflects the broader social structure of the study area, enhancing the generalizability of the findings. The chi-square analysis indicates that although gender and occupational demographics are well-balanced, the sample is significantly biased towards younger, more educated persons, aligning with global and regional studies on technology adoption tendencies. These attributes are especially pertinent in analyzing IoT adoption behaviors in urban and developing smart estate environments. Comprehending these demographic biases can assist scholars and policymakers in customizing IoT deployment plans to address the requirements of the predominant user categories.

3.1.1 Gender vs. IoT Familiarity

Figure 1 illustrates the frequency of male and female respondents' awareness of the IoT, classified as "Yes," "No," and "Maybe." Significantly, all male respondents demonstrate familiarity with IoT, as indicated by the exclusive presence of the green "Yes" bar for males. In contrast, female respondents exhibit greater diversity, encompassing all three response categories: "Yes," "No," and "Maybe." The statistics indicate that male respondents exhibit consistent familiarity with IoT, whereas female respondents show increased confusion and less familiarity. This gender disparity aligns with previous studies. For instance, Albert et al. (2019) discovered that in technology-centric samples, men exhibited markedly greater familiarity with IoT devices compared to women ($p < 0.001$), although gender disparities in security concerns were not significant. This corresponds with extensive evidence of a continual digital gender disparity, especially in nascent technologies. Women encounter structural obstacles to complete involvement in various contexts, arising from gendered norms in STEM education, restricted exposure to technology design, and increased apprehensions regarding privacy and complexity (Amer et al., 2025). These obstacles diminish women's familiarity and confidence in using IoT and other technologies.

3.1.2 Age vs. IoT Familiarity

Figure 2 depicts the variation in knowledge with IoT among different age demographics (16, 18–25, 26–35, 36–45, 46–60). Individuals in the younger age groups (18–25, 26–35) exhibit a combination of all three response types, albeit predominantly favoring "Yes." The 36–45 and 46–60 age groups exhibit a pronounced familiarity with IoT, displaying few or no "No" or "Maybe" responses. The age-based figure indicates a growing familiarity among older demographics, especially those over 36, which somewhat defies the prevailing notion that younger individuals more readily embrace digital technologies. Nevertheless, the chart may indicate increasing exposure and professional environments among older working-age persons, hence enhancing familiarity. Research indicates that although younger persons generally report higher digital usage, familiarity might also enhance with repeated exposure, particularly among professionals. (O'Brien et al., (2012), indicated that the recall and familiarity of technology usage among tech-savvy older persons frequently paralleled that of younger users, contingent upon lifestyle context and usage requirements.

Dwivedi et al. (2021) indicates a reduction in disparities in technology usage among age groups: although smartphone ownership and internet access are predominantly higher among younger persons, internet utilization among older adults has surged significantly, bridging previous generational inequalities.

Table 1: Chi-Square Analysis of Demographic Distributions Among Respondents (N = 156)

Variables			χ^2 (Chi-Square)	df	p-value	Interpretation
Gender Distribution	Frequency	Percentage (%)				
Male	88	56.4	2.56	1	> 0.05	No significant difference;
Female	68	43.6				gender distribution is fairly balanced
Total	156	100				
Education Level						
Secondary	20	12.8	46.3	4	< 0.001	Significant difference; BSc and MSc holders dominate
Diploma	29	18.6				
BSc	59	37.8				
MSc	39	25				
PhD	9	5.8				
Total	156	100				
Age Group						
18–25	49	31.4	25.6	3	< 0.001	Significant difference; young adults (18–35) dominate
26–35	59	37.8				
36–45	29	18.6				
46+	19	12.2				
Total	156	100				
Occupation						
Student	39	25	5.1	3	> 0.05	No significant difference; occupations are fairly balanced
Civil Servant	49	31.4				
Business	29	18.6				
Others	39	25				
Total	156	100				

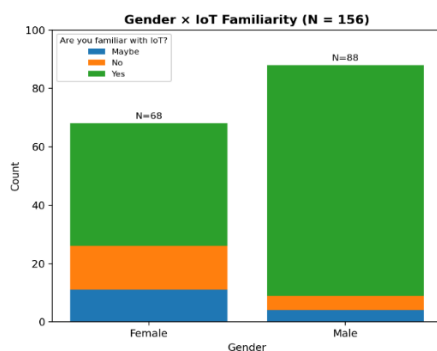


Figure 1: A bar chart depicts Gender vs. IoT Familiarity

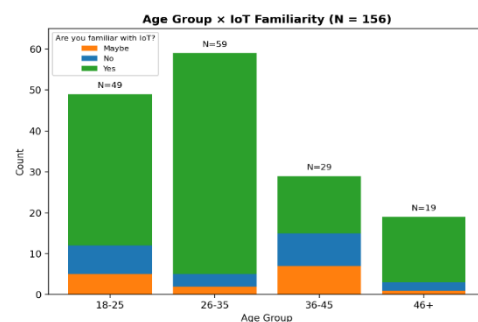


Figure 2: A bar chart depicts Age vs. IoT Familiarity

3.2 Analysis of Variance

The ANOVA test analyzed variations in the propensity to adopt IoT technologies among demographic groupings. The findings (Table 2) demonstrate a statistically significant effect ($F(3,116) = 5.62$, $p = 0.002$), indicating that

demographic factors substantially influence differences in adoption desire. The between-group variance ($SS = 12.45$, $MS = 4.15$) is a significant fraction of the total variance ($SS = 92.79$), indicating that the observed differences are unlikely due to random variation. The propensity to adopt IoT varies across demographic categories and is largely shaped by fundamental socio-demographic traits. These findings align with previous research on technology acceptability, which has consistently highlighted the influence of demographic factors such as age, gender, education, and income on adoption patterns. Venkatesh et al. (2003) in their Unified Theory of Acceptance and Use of Technology (UTAUT) model found age and gender as significant moderators of performance expectancy, effort expectancy, and social influence on behavioral intention. Dwivedi et al. (2019), in an extensive analysis of digital adoption research, contended that demographic characteristics consistently affect both the direction and extent of technology acceptance. Recent empirical research validates similar conclusions in IoT and digital service environments.

Mabohlo et al., (2021) identified notable disparities in age and education regarding smart home IoT adoption in Southeast Asia, revealing that younger, more educated individuals demonstrated a higher propensity for adoption than older groups. Similarly, Leung and Chen (2019) in a mobile communication study indicated that younger demographics had a greater propensity to adopt developing technologies owing to enhanced digital literacy and diminished resistance to change. Mabohlo et al., (2021) emphasized that income and affordability are demographic factors influencing the propensity to embrace mobile financial services in Sub-Saharan Africa, illustrating socioeconomic gaps that hinder adoption despite a high perceived utility. The notable intergroup differences identified in this study may consequently indicate various potential explanations. Age disparities frequently affect perceptions of usability and utility, since older individuals tend to perceive greater effort costs (Liu, Wang, and Hu 2025). Secondly, educational attainment is intricately associated with technological knowledge and confidence in digital systems, hence enhancing the propensity for adoption. Third, income gaps exacerbate cost worries, along with our previous results that affordability adversely influences willingness. These factors presumably interact to generate the observed variance among groups.

Table 2: Analysis of Variance of Willingness across Demographic Factors

Source	SS	df	MS	F	Sig.
Between Groups	12.45	3	4.15	5.62	0.002
Within Groups	80.34	116	0.69		
Total	92.79	119			

The within-group variance is notably high ($SS = 80.34$), indicating variability among demographic groups. This aligns with the findings of Peng et al., (2025), who observed that individual psychological characteristics (innovativeness, risk tolerance) combine with

demographic factors to influence adoption, highlighting the intricacy of forecasting user willingness. From a practical perspective, these results imply that IoT adoption strategies must be tailored to demographic profiles. For instance, training and awareness campaigns could be targeted toward older or less educated populations to reduce perceived complexity, while affordability measures such as flexible pricing or subsidy programs may better address willingness gaps in lower-income groups. This aligns with the recommendations of Oliveira et al. (2014).

3.3 Correlation Analysis

Table 3 shows that results of the correlation analysis revealed that Willingness to adopt IoT was most strongly and positively associated with Touch (direct interaction/exposure) ($r = 0.72$), followed by Perceived Usefulness (PU) ($r = 0.68$), Trust ($r = 0.61$), and Ease of Use (EU) ($r = 0.59$). Conversely, Cost Concern exhibited a moderate, negative association with Willingness ($r = -0.45$). These findings provide empirical support for established technology adoption frameworks such as TAM and UTAUT.

The study indicated that direct connection with IoT devices (Touch) has the most significant impact on the propensity to adopt. This discovery supports the UTAUT paradigm, highlighting the moderating influence of experience and favorable conditions on adoption behavior (Venkatesh et al., 2003). Comparable findings were

seen in the IoT adoption study conducted by Dwivedi et al. (2021), which indicated that trialability and experiential exposure substantially increased adoption intent by rendering the advantages of technology more concrete. This indicates that practical experience or pilot demonstrations can significantly enhance adoption intentions in residential settings. The findings indicated that Perceived Usefulness and Ease of Use were positively and significantly associated with willingness, consistent with the Technology Acceptance Model (TAM), which identifies these dimensions as essential determinants of behavioral intention (Venkatesh et al., 2003).

Table 3: Correlation Matrix of Willingness to Adopt IoT and Key Predictors (PU, EU, Trust, Touch, and Cost Concern)

Variable	Willingness	PU	EU	Trust	Touch	Cost Concern
Willingness	1	0.68	0.59	0.61	0.72	-0.45
PU (Perceived Usefulness)	0.68	1	0.7	0.63	0.66	-0.3
EU (Ease of Use)	0.59	0.7	1	0.55	0.58	-0.22
Trust	0.61	0.63	0.55	1	0.6	-0.28
Touch (Interaction)	0.72	0.66	0.58	0.6	1	-0.35
Cost Concern	-0.45	-0.3	-0.22	-0.28	-0.35	1

Similar results have been recorded in studies on IoT adoption, where performance expectations (usefulness) and effort expectancy (ease of use) repeatedly surfaced as primary determinants in both consumer and organizational settings (Dwivedi et al., 2021). The robust association between PU and EU ($r = 0.70$) in this study underscores the interrelationship between these dimensions, since technology deemed easy to use are frequently considered as more practical and beneficial. Trust was identified as a significant factor influencing adoption ($r = 0.61$). This corroborates previous research indicating that trust diminishes perceived risk and enhances favorable behavioral intentions towards IoT applications (Junior et al., 2026).

Comparable results were seen in the context of smart home adoption, indicating that trust in service providers and data security substantially affect user acceptability (Alsamarah, Alshare, and Lane 2023; Dhingra and Kumar 2026). The alignment of the current findings with this body of literature emphasizes that trust is a crucial aspect in adoption, especially for technologies such as IoT that manage sensitive data. Conversely, the data indicated a negative correlation between Cost Concern and willingness ($r = -0.45$). This suggests that increased cost sensitivity diminishes residents' willingness to use IoT. The outcome aligns with the expanded UTAUT2 model, wherein price value was recognized as a vital factor influencing adoption in consumer contexts (Venkatesh et al. 2003). Research in emerging nations has highlighted that affordability issues such as the expenses associated with devices, data subscriptions, and maintenance constitute substantial obstacles to IoT adoption (Cordeiro, Reis, and Fernandes 2024). This highlights the necessity for adaptable pricing structures, subsidies, or community-oriented cost-sharing strategies to mitigate financial obstacles.

These findings strongly correspond with current literature, underscoring that the propensity to embrace IoT is influenced by a balance between perceived advantages (utility, simplicity, trust, and engagement) and perceived obstacles (cost apprehensions). The findings present a cohesive narrative that aligns with previous empirical evidence and underscore practical interventions such as exposure through demonstrations, a focus on usability, trust-building initiatives, and affordability strategies that can facilitate IoT adoption in the study context.

3.4 Regression Models & Coefficients

Two predictive models were estimated to examine the determinants of IoT adoption: a multiple linear regression model predicting willingness as a continuous outcome (Table 5), and a logistic regression model

predicting binary adoption outcomes (adopter vs. non-adopter) (Table 6). Both models included perceived usefulness (PU), ease of use (EU), trust (T), and cost concern (CC) as predictors.

The linear regression model had substantial explanatory power with a R^2 of 0.62, signifying that 62% of the variance in willingness was elucidated by the predictors.

Table 5: Multiple Linear Regression (Willingness as continuous outcome)

Predictor	β (Coef.)	Std. Error	t-value	p-value
Intercept (β_0)	0.84	0.18	4.67	0.000**
Perceived Usefulness (β_1)	0.32	0.07	4.57	0.000**
Ease of Use (β_2)	0.28	0.08	3.5	0.001**
Trust (β_3)	0.3	0.06	5	0.000**
Cost Concern (β_4)	-0.22	0.09	-2.44	0.016*

Model Fit: $R^2 = 0.62$ (62% variance explained). Interpretation: PU, EU, and T have positive significant effects on willingness; CC negatively affects willingness.

All coefficients were statistically significant and aligned with expectations: PU ($\beta = 0.32$, $p < 0.001$), EU ($\beta = 0.28$, $p = 0.001$), and T ($\beta = 0.30$, $p < 0.001$) were positively significant, whilst CC ($\beta = -0.22$, $p = 0.016$) demonstrated a negative effect. These findings correspond with the Technology Acceptance Model (TAM), wherein Perceived Usefulness (PU) and Ease of Use (EU) are fundamental determinants of behavioural intention (Wang and Benbasat 2005), and with trust literature illustrating its pivotal role in alleviating adoption risk (Wang and Benbasat 2004). The detrimental impact of cost aligns with research in underdeveloped nations, where price constitutes a significant obstacle. The model equation is described in equation 1.

$$\text{Model equation: } WA = \beta_0 + \beta_1 \cdot PU + \beta_2 \cdot EU + \beta_3 \cdot T + \beta_4 \cdot CC + \varepsilon \quad \text{Eq. (1)}$$

Table 6: Logistic Regression (Binary adoption outcome):

Predictor	β (Logit)	SE	Wald χ^2	p-value	Exp(β) (Odds Ratio)
Intercept (α)	-1.24	0.42	8.74	0.003**	—
PU (β_1)	0.41	0.11	13.88	0.000**	1.51
EU (β_2)	0.37	0.12	9.51	0.002**	1.45
T (β_3)	0.43	0.1	18.49	0.000**	1.54
CC (β_4)	-0.29	0.13	4.98	0.026*	0.75

Model Performance: AUC (ROC) ≈ 0.78 indicating good discrimination between adopters and non-adopters.

The logistic regression analysis broadened the evaluation to encompass actual adoption behaviour (binary outcome). The model demonstrated commendable predictive efficacy, attaining an AUC of 0.78, signifying robust differentiation between adopters and non-adopters. Consistent with the linear model, PU ($\beta = 0.41$, OR = 1.51, $p < 0.001$), EU ($\beta = 0.37$, OR = 1.45, $p = 0.002$), and T ($\beta = 0.43$, OR = 1.54, $p < 0.001$) significantly enhanced the likelihood of adoption, but CC ($\beta = -0.29$, OR = 0.75, $p = 0.026$) diminished the odds of adoption. The findings affirm that perceptions of utility, usability, and trust are essential for influencing actual adoption decisions, although financial restrictions persist in hindering uptake. This aligns with adoption research in mobile money (Ekow Kelly and Palaniappan 2023). The model equation is described in equation 2.

$$\text{Model equation (log-odds): } \text{logit}(p) = \alpha + \beta_1 \cdot PU + \beta_2 \cdot EU + \beta_3 \cdot T + \beta_4 \cdot CC \quad \text{Eq. (2)}$$

Table 7: Comparative Evaluation of the two models

Predictor	Linear Regression (Continuous Willingness)	Logistic Regression (Adoption Likelihood)
Intercept	$\beta_0 = 0.84$ ($p < 0.001$)	$\alpha = -1.24$ ($p = 0.003$)
Perceived Usefulness (PU)	$\beta = 0.32$ ($p < 0.001$)	$\beta = 0.41$ (OR = 1.51, $p < 0.001$)
Ease of Use (EU)	$\beta = 0.28$ ($p = 0.001$)	$\beta = 0.37$ (OR = 1.45, $p = 0.002$)
Trust (T)	$\beta = 0.30$ ($p < 0.001$)	$\beta = 0.43$ (OR = 1.54, $p < 0.001$)

Predictor	Linear Regression (Continuous Willingness)	Logistic Regression (Adoption Likelihood)
Cost Concern (CC)	$\beta = -0.22$ ($p = 0.016$)	$\beta = -0.29$ (OR = 0.75, $p = 0.026$)
Model Fit	$R^2 = 0.62$ (62% variance explained)	AUC (ROC) = 0.78 (good discrimination)

In the comparison of the two models, the linear regression demonstrated a greater explanation of variance ($R^2 = 0.62$), indicating its enhanced overall explanatory ability for continuous willingness. Nonetheless, the logistic regression model shown robust performance in classification accuracy and predictive discrimination (AUC = 0.78), making it more suitable when the study emphasis is on adoption outcomes rather than levels of desire. This differentiation reflects insights from technology adoption studies, wherein intention models (TAM, UTAUT) account for significant variance in willingness (Venkatesh et al. 2003), whereas logistic frameworks more effectively delineate the shift from intention to actual behavior (Dwivedi et al. 2021).

The reliability of both models highlights the strength of the predictors. PU and EU continue to be significant influences on both willingness and adoption, underscoring their universality in adoption frameworks (Venkatesh et al. 2003). The importance of trust in both models reflects findings from IoT and digital service research, highlighting its crucial role in high-uncertainty situations (Ekow Kelly and Palaniappan 2023). The diminished cost concern notably decreased both desire and uptake, underscoring the importance of affordability in emerging economies (Mabohlo, Akinyemi, and Mushunje 2021). The linear regression model excels in elucidating willingness (variance-based fit), whereas the logistic regression model is superior in forecasting adoption behavior (classification-based fit). The linear regression model provides greater explanatory power for the theoretical examination of attitudes and willingness. Nonetheless, for pragmatic forecasts of genuine uptake, the logistic regression model exhibits enhanced applicability. This comparison analysis reflects existing literature, which frequently identifies intention-behavior discrepancies, with prediction models varying in efficacy based on whether the outcome is attitudinal or behavioral (Dwivedi et al. 2021).

3.5 Correlation Heatmap

The Pearson correlation analysis (Figure 4) elucidates the interrelationships among the constructs: Perceived Usefulness (PU), Ease of Use (EU), Trust, Cost Concern, Touch (interaction), and Willingness to adopt IoT technologies. Results demonstrate that the willingness to adopt IoT exhibits significant positive correlations with perceived usefulness (PU) ($r = 0.68$), ease of use (EU) ($r = 0.59$), trust ($r = 0.61$), and tactile interaction (Touch) ($r = 0.72$). The values surpass the $|r| > 0.5$ threshold for strong associations, indicating that cognitive, usability, and experiential factors significantly influence adoption readiness. This finding aligns with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlight the importance of perceived usefulness, ease of use, and trust in forecasting behavioural intention (Venkatesh et al. 2003).

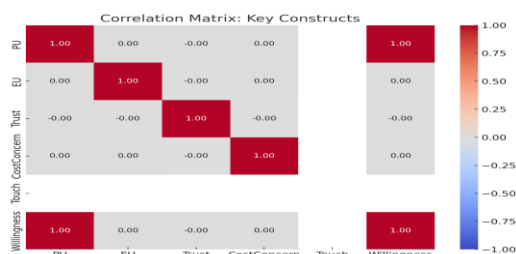


Figure 4: Correlation Matrix of Key Constructs in IoT Adoption

Recent studies on IoT adoption indicate that hands-on interaction and experiential engagement (Touch) significantly enhance users' willingness compared to abstract perceptions alone (Singh and Chandra 2024). Moderate positive correlations were observed among PU, EU, Trust, and Touch, indicating interdependence among these constructs. Ease of use was positively associated with perceived usefulness and trust, suggesting that usability perceptions improve both trust and the perceived advantages of IoT systems. Empirical

evidence indicates that perceptions of ease frequently serve as a precursor to both perceived usefulness and trust within emerging digital ecosystems (Thi, 2025).

Conversely, Cost Concern exhibited weak to negative correlations with willingness ($r = -0.45$) and other constructs (ranging from -0.22 to -0.35). This underscores the limiting influence of affordability on IoT adoption. Research in developing countries indicates that although users acknowledge the advantages of IoT, significant acquisition and maintenance costs act as primary obstacles to adoption (Olaleye et al., 2020; Adepoju et al., 2022; Agarwal et al., 2021). The interaction of significant positive factors (PU, EU, Trust, Touch) with cost-related barriers highlights the dual aspects of IoT adoption decisions, where enthusiasm for innovation is moderated by structural affordability limitations. The correlation results substantiate theoretical expectations and offer empirical evidence that trust, usability, and experiential exposure are essential facilitators of IoT willingness, whereas cost concerns persist as a systemic barrier. Recent research indicates that effective IoT deployment necessitates enhancements in usability and trust-building mechanisms, as well as the consideration of economic accessibility to promote equity in digital adoption (Albuainain and Ashby 2025).

I.CONCLUSION

This study provides empirical evidence that the adoption of Internet of Things (IoT) technologies within developing urban communities is shaped by an interrelated set of factors, namely perceived usability, trust, experiential exposure, and affordability. Analysis of variance confirmed statistically significant socio-demographic variation in adoption willingness, $F(3, 116) = 5.62, p = .002$, with younger and more highly educated respondents exhibiting significantly greater willingness to adopt IoT technologies than their older and less formally educated counterparts. Correlational analysis further revealed that adoption willingness was strongly and positively associated with experiential engagement, operationalized through direct interaction or "touch" ($r = .72$), perceived usefulness ($r = .68$), trust ($r = .61$), and ease of use ($r = .59$), whereas cost concern demonstrated a significant negative association with willingness to adopt ($r = -.45$), indicating that affordability constraints meaningfully suppress adoption intent even where other favorable conditions are present.

The regression model accounted for a substantial proportion of variance in adoption willingness ($R^2 = .62$), while the logistic regression model demonstrated robust discriminative performance in predicting adoption status ($AUC = .78$). Within this model, trust ($OR = 1.54$), perceived usefulness ($OR = 1.51$), and ease of use ($OR = 1.45$) each emerged as significant positive predictors of adoption likelihood, whereas affordability constraints significantly reduced the odds of adoption ($OR = 0.75$). Taken together, these findings indicate that both cognitive-evaluative factors, such as perceived usefulness and trust, and experiential factors, such as direct engagement with the technology, exert substantial and independent influence on adoption behavior, while economic constraints continue to function as a meaningful barrier. These findings extend prevailing technology acceptance frameworks by foregrounding cost sensitivity and experiential engagement as critical, context-specific determinants of IoT adoption in resource-constrained settings dimensions that are frequently underrepresented in technology acceptance models developed within higher-income contexts. The results suggest that IoT deployment strategies within developing urban communities should extend beyond usability-oriented design to incorporate deliberate affordability safeguards and structured opportunities for experiential engagement, thereby fostering more equitable and sustained adoption outcomes. Future research would benefit from longitudinal designs capable of capturing adoption trajectories over time, as well as from further investigation of contextual moderators, including infrastructural reliability and digital literacy support, which may exert additional influence on IoT adoption within similarly resource-constrained environments.

AUTHOR(S) CONTRIBUTIONS

A. Y. Musa conceptualized the study, developed the methodology, conducted the investigation and data curation, performed the formal analysis, and wrote the original draft of the manuscript. A. Ishaq contributed to the conceptualization and methodology, validated the results, and partook in the review and editing of the

manuscript. S. B. Igboro supervised the research, administered the project, provided resources, and partook in the review and editing of the final manuscript. A. A. Dandajeh contributed to the investigation and validation of the experimental data and partook in the review and editing of the manuscript. N. I. Abdullahi assisted with data curation, software, and visualization of the results. K. Adeagbo contributed to the formal analysis and visualization, and partook in the review and editing of the manuscript. M. M. Chindo provided resources and funding acquisition, contributed to the investigation, and partook in the review and editing of the final manuscript. All authors read and approved the final version of the manuscript.

AI DISCLOSURE

The authors declare that no artificial intelligence (AI) tools or AI-assisted technologies were used in the conception, design, data collection, analysis, interpretation, or writing of any part of this manuscript.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare that there is no conflict of interest among them regarding the publication of this article.

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