Perceived Ease of Use and Actual System Usage as Drivers of Operational Efficiency: Evidence from the National Insurance Corporation of Tanzania

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ABSTRACT

Insurers in emerging markets continue to invest heavily in information technology (IT), yet the mechanism through which such investment translates into operational performance remains poorly understood. Drawing on the Technology Acceptance Model (TAM), this study examines the effects of perceived usefulness, perceived ease of use, and actual system usage of IT on the operational efficiency of the National Insurance Corporation of Tanzania (NIC). The researcher administered a cross-sectional survey to 89 headquarters employees selected through stratified random sampling. The data were analyzed using confirmatory factor analysis, correlation, multiple regression, and a supplementary parallel mediation analysis with bootstrapped confidence intervals, and both common-method variance and differences across occupational levels were assessed. The three constructs jointly explained 39.6% of the variance in operational efficiency, $F(3, 85) = 18.60$, $p < .001$. Perceived ease of use ($\beta = .438$, $p = .002$) and actual system usage ($\beta = .287$, $p = .040$) had significant independent effects, whereas perceived usefulness did not ($\beta = -.096$, $p = .381$). The mediation analysis indicated that perceived usefulness was associated with operational efficiency indirectly, mainly through ease of use (indirect effect = 0.221, 95% bootstrap CI [0.046, 0.409]). Ease of use and system usage were, however, empirically difficult to separate, and the cross-sectional, self-reported data limit causal inference. The findings extend TAM from behavioral intention to a function-level measure of organizational performance in an under-researched African insurance context. In practice, insurers seeking efficiency gains from IT should prioritize system usability, continuous training, responsive technical support, and routine system use before spending more on system capability.

Keywords: Technology Acceptance Model, perceived ease of use, actual system usage, operational efficiency, insurance

INTRODUCTION

Insurance firms depend on accurate and timely information to price risk, settle claims fairly, and remain solvent, which makes them natural beneficiaries of information technology (IT). Predictive analytics and automated underwriting platforms allow insurers to evaluate applicants against historical claims patterns, shorten decision cycles, and process higher application volumes without a proportional increase in staff (Agarwal et al., 2022; Kanapathipillai et al., 2024). Digitized claims workflows reduce the manual handling that historically delayed settlement, while machine-learning-based fraud detection flags anomalous claims that a manual reviewer might miss (Eckert et al., 2022; Kaur & Singh, 2023). Software-based actuarial modeling and digital policy administration platforms similarly support more accurate reserving, faster renewals, and earlier identification of emerging risk exposures (Nsour et al., 2023; Wanjohi & Waithaka, 2024).

These gains do not come automatically. They depend on data quality, staff capability, and infrastructure reliability, conditions that vary considerably across emerging markets (Moyo et al., 2022). Just as important,

installing a system does not mean that it is used well. A panel study of the Insurance Management Information System (IMIS) in Tanzania found that, although the system was mandated for every facility in its coverage area, reported claims fell short of expected claims by a median of 77.8%, with adoption varying with management quality and workload rather than with the technology itself (Schuetze et al., 2023). Likewise, policyholder resistance to insurance chatbots has been traced to low perceived ease of use and low trust, not to a lack of access to the technology (de Andrés-Sánchez & Gené-Albesa, 2023). In short, IT's impact on performance depends on how people perceive and use the systems, not just on the systems themselves.

Tanzania's insurance sector offers a timely setting for examining this proposition. According to the Tanzania Insurance Regulatory Authority (TIRA), the number of registered insurance service providers rose from 1,165 in 2022 to 1,549 in 2023, gross premiums written increased by 7.4% to TZS 1.24 trillion, and sector assets grew from TZS 1.697 trillion to TZS 2.152 trillion (TIRA, 2024). Growth has been accompanied by a regulatory push toward digitization, including the requirement that insurers submit operational data through TIRA's Management Information System (TIRAMIS) (TIRA, 2022). Yet operational friction persists. In 2022, TIRA received 332 policyholder complaints, of which 186 concerned claims settlement delays exceeding 45 days; the Insurance Group of Tanzania (82), Resolution Insurance Limited (36), and the National Insurance Corporation of Tanzania (NIC) (24) together accounted for 142 complaints (42.8%) (TIRA, 2022).

NIC is one of Tanzania's oldest and most established insurers and has invested in IT across underwriting, claims processing, actuarial services, policy management, and risk assessment over an extended period. Its moderate complaint record, concentrated in core service functions despite sustained IT investment, makes it a useful case for observing, instead of assuming, the link between IT and operational performance. Existing studies of technology acceptance in insurance have largely been conducted outside East Africa and have mostly stopped at attitude or behavioral intention as the outcome (Gharakhani & Pourhashemi, 2020; Huang et al., 2019; Pham et al., 2022; Toukabri & Ettis, 2021). Where organizational performance has been measured directly, it has typically been treated as a single undifferentiated outcome (Habeeb et al., 2021; Malit & Muendo, 2017; Mueni & Angima, 2022). This study addresses that gap by applying the Technology Acceptance Model (TAM) to NIC's core operational functions. Specifically, it examines (i) the effect of perceived usefulness of IT on operational efficiency, (ii) the effect of perceived ease of use of IT on operational efficiency, and (iii) the effect of actual system usage of IT on operational efficiency. By modeling the three TAM constructs jointly against a function-level measure of operational efficiency, the study identifies where in the acceptance chain IT investment converts, or fails to convert, into measurable performance. The study contributes empirical evidence from an under-researched African insurance market and offers insurers and regulators a diagnostic basis for directing future IT investment.

LITERATURE REVIEW

Theoretical framework: the Technology Acceptance Model

TAM was developed by Davis (1986) in his doctoral work at the Massachusetts Institute of Technology and introduced to the wider research community through Davis (1989). The model proposes that an individual's use of an information system is shaped by two core beliefs: perceived usefulness, the degree to which a person believes that using a system will enhance their job performance, and perceived ease of use, the degree to which a person believes that using the system will be free of effort. These beliefs shape attitude toward using the system and behavioral intention, which in turn predicts actual system usage (Davis, 1989; Davis et al., 1989). Subsequent extensions, most notably the Unified Theory of Acceptance and Use of Technology, have incorporated social influence and facilitating conditions while retaining the central role of usefulness and ease of use (Venkatesh et al., 2003, 2016).

TAM's principal strength is its parsimony: it reduces technology acceptance to a small number of clearly measurable constructs that have been tested extensively across technologies and settings (Bothma & Mostert, 2023; Marikyan & Papagiannidis, 2023). Its main limitations follow from the same parsimony. The model gives limited weight to organizational and infrastructural conditions, assumes broadly linear relationships among its constructs, and focuses on initial adoption rather than on sustained use or downstream outcomes

(Ajibade, 2018; Du et al., 2024; Mondego & Gide, 2022). The literature's general recommendation is therefore not to discard TAM but to extend it to new contexts and outcomes (Marikyan & Papagiannidis, 2023; Osman Opoku & Enu-Kwesi, 2020). Alternative frameworks such as the Theory of Planned Behavior (Ajzen, 1991) and Diffusion of Innovations theory (Rogers, 2003) explain behavior more generally or at the population level. TAM was preferred here because it is purpose-built for individual-level technology acceptance within organizations and its constructs map directly onto the study's objectives.

Perceived usefulness and organizational performance

Perceived usefulness is consistently reported as one of the strongest predictors of attitude and intention toward insurance technology. Naicker and Van Der Merwe (2018) found that perceived usefulness and ease of use positively influenced managers' adoption of mobile technology in the South African life insurance industry, while perceived cost and complexity had negative effects. Gharakhani and Pourhashemi (2020) reported similar positive effects of usefulness and ease of use on attitude and intention toward mobile insurance in Iran. At the organizational level, Malit and Muendo (2017) found that ICT strategy implementation improved the performance of insurance firms in Kenya, and Sibindi (2022) linked ICT diffusion to life insurance market development across sub-Saharan Africa. Grounded in TAM and these findings, the study hypothesizes:

H1: Perceived usefulness of IT has a significant positive effect on operational efficiency.

Perceived ease of use and organizational performance

Perceived ease of use influences outcomes both directly and through its effect on perceived usefulness. Toukabri and Ettis (2021) found that ease of use significantly increased the perceived usefulness of e-insurance in Saudi Arabia, and usefulness then shaped attitude and intention. Huang et al. (2019) showed that ease of use, usefulness, trust, and product involvement predicted attitudes toward online insurance in Taiwan, particularly for routine products. Pham et al. (2022) reported that trust, ease of use, and usefulness significantly increased Vietnamese customers' intention to use insurance apps. At the firm level, Mueni and Angima (2022) found a positive and significant relationship between digital adoption and the performance of Kenyan insurers, operating through faster claims processing and improved service delivery. Accordingly:

H2: Perceived ease of use of IT has a significant positive effect on operational efficiency.

Actual system usage and organizational performance

Actual system usage captures what people do with a system, not what they think of it, and it is the construct closest to realized performance. Hammouri et al. (2021) found that usefulness, ease of use, IT background, and social influence shaped the adoption of an electronic health insurance administration system in Jordan. Wang et al. (2019) showed that service availability, usefulness, and ease of use influenced attitude toward mobile health insurance in Indonesia, which in turn increased intention and actual usage; interestingly, perceived usefulness had no direct positive effect on intention once attitude was accounted for. Habeeb et al. (2021) found a significant positive association between IT implementation and organizational performance at an Iraqi insurance company, while Sabu (2023) documented efficiency gains, cost reductions, and improved risk assessment from technology use across the insurance industry. Hence:

H3: Actual system usage of IT has a significant positive effect on operational efficiency.

Constraints on IT adoption in insurance

The literature also identifies structural constraints that limit the conversion of IT investment into performance. Insurers hold large volumes of sensitive customer data and are therefore attractive targets for cyberattacks; IBM (2023) placed the global average cost of a data breach at USD 4.45 million, with financial services among the costlier sectors affected. Workforce apprehension about automation, constrained IT budgets, uneven staff training, and the need to integrate new systems with legacy infrastructure further weaken the link between investment and performance (Kanapathipillai et al., 2024; Krishnakanthan et al., 2019; Tang & Niu, 2023).

Taken together, these constraints suggest that deploying a system is only the first step; its effect on performance depends on how staff perceive it and use it.

Research gap and conceptual framework

Three gaps emerge from the reviewed literature. First, no reviewed study examines the TAM constructs in the Tanzanian insurance sector. Second, most insurance-sector TAM studies measure attitude or behavioral intention rather than organizational performance, even though intention is only a proxy for the behavior that ultimately affects performance. Third, studies that do measure organizational performance treat it as a single outcome and do not break it down into the operational functions, namely underwriting, claims processing, actuarial work, policy management, and risk assessment, in which an insurer's efficiency is actually determined. Figure 1 presents the conceptual framework that addresses these gaps by testing the three TAM constructs jointly against a function-level measure of operational efficiency.

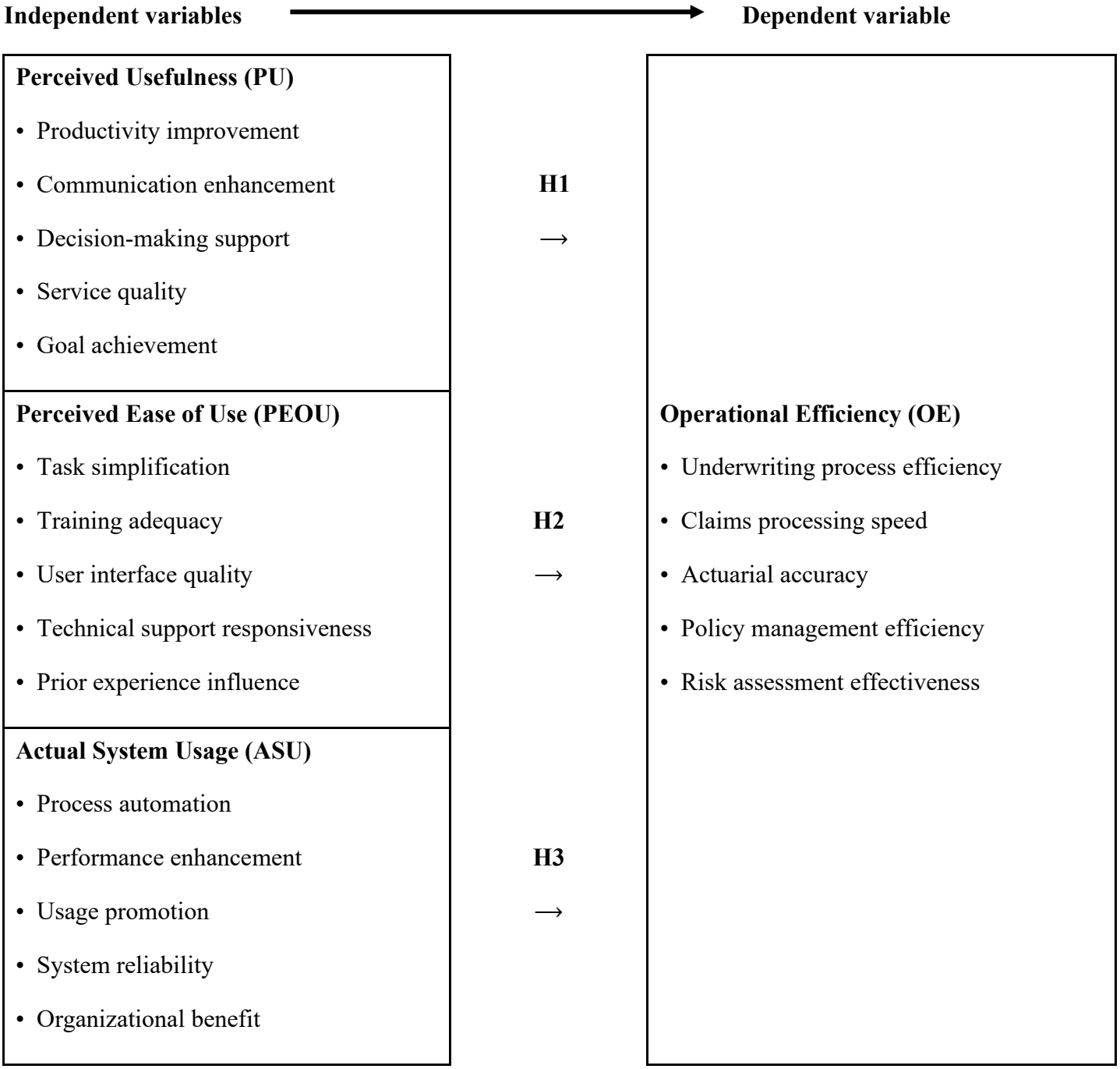

Figure 1: Conceptual framework
Source: Adapted from Davis (1989).

METHODOLOGY

Research design and study setting

The study adopted a quantitative, cross-sectional survey design within a single-case setting (Saunders et al., 2023). The case was NIC's headquarters in Dar es Salaam, which houses the corporation's management, finance and investment, human resources and administration, ICT, general insurance, life insurance, marketing and communication, procurement, legal, risk, actuarial, and internal audit functions. The case boundary allowed an in-depth examination of one organization, while the survey strategy produced standardized data suitable for statistical analysis (Borgstede & Scholz, 2021; Taherdoost, 2022).

Population, sample size, and sampling

The target population comprised all 115 employees at NIC headquarters across four occupational categories: directors and heads of unit, section managers, ICT officers, and general users of IT systems. The minimum sample size was determined using the Yamane (1967) formula at a 5% margin of error:

$$n = N / [1 + N(e)^2] = 115 / [1 + 115(0.05)^2] = 89.32 \approx 89$$

Stratified sampling was used to ensure that every occupational group was represented, with respondents selected at random within each stratum (Parsons, 2017). Data collection continued until 89 valid responses had been obtained. Because senior staff were harder to reach, the achieved sample departs from strict proportional allocation, with directors and ICT officers somewhat under-represented and general users somewhat over-represented (Table 1).

A chi-square goodness-of-fit test nevertheless showed that the occupational composition of the sample did not differ significantly from that of the headquarters population, $\chi^2(3) = 1.48$, $p = .687$, because general users also make up most of the population (71.3%). However, the absolute number of senior respondents was small (n = 10: five directors or heads of unit and five section managers), which limits comparisons across hierarchical levels.

Table 1: Population and achieved sample by occupational category

Occupational category	Population	Valid responses	Share of sample (%)
Director / Head of unit	10	5	5.6
Section manager	7	5	5.6
ICT officer	16	11	12.4
General user	82	68	76.4
Total	**115**	**89**	**100**

Source: Field data (2024).

Measurement and instrument

Data were collected through a structured, closed-ended questionnaire administered in person. Each of the four constructs was measured with five items on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Likert, 1932). Items for perceived usefulness, perceived ease of use, and actual system usage were adapted from the TAM construct definitions of Davis (1989), and items for operational efficiency were developed from the operational performance dimensions described by Slack and Brandon-Jones (2019),

covering underwriting efficiency, claims processing speed, actuarial accuracy, policy management, and risk assessment.

Construct scores were computed as the mean of each construct's items; treating such summated scale scores as approximately interval-level data for parametric analysis is well supported in the methodological literature (Norman, 2010). To reduce common-method and social desirability bias at the design stage, the questionnaire was anonymous, respondents were assured that there were no right or wrong answers, predictor and outcome items were placed in separate sections, and item wording was checked for ambiguity in the pilot study (Podsakoff et al., 2003).

The questionnaire was piloted in April 2024 with nine employees drawn from the four strata (approximately 10% of the main sample) to check the clarity of wording, the adequacy of response options, and completion time. Item wording was refined where necessary, and pilot respondents were excluded from the final sample.

Data analysis

Data were analyzed using IBM SPSS Statistics version 26. The confirmatory factor analysis and the bootstrap mediation analysis, which are not part of the base SPSS package, were run in Python. Descriptive statistics summarized respondents' profiles and perceptions. Internal consistency was assessed using Cronbach's (1951) alpha, with .70 as the minimum acceptable value, and a principal components analysis (PCA) of the three IT construct scores was used to examine their shared variance (Hair et al., 2019). Construct validity was then examined at the item level through a four-factor confirmatory factor analysis (CFA), estimated by maximum likelihood with the semopy package (Igolkina & Meshcheryakov, 2020).

Model fit was judged with the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) (Hu & Bentler, 1999). Convergent validity was assessed with composite reliability (CR $\geq$ .70) and average variance extracted (AVE $\geq$ .50), and discriminant validity with the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait (HTMT) ratio of correlations, for which values above .85 (conservative) or .90 (liberal) indicate insufficient discriminant validity (Henseler et al., 2015). Pearson correlation coefficients assessed the bivariate relationships among the constructs, interpreted using Cohen's (2013) benchmarks of .10, .30, and .50 for small, medium, and large effects. Multiple linear regression estimated the independent effect of each construct while holding the others constant:

$$OE = \beta 0 + \beta 1PU + \beta 2PEOU + \beta 3ASU + \varepsilon$$

where OE is operational efficiency, PU is perceived usefulness, PEOU is perceived ease of use, ASU is actual system usage, $\beta 0$ is the intercept, $\beta 1$ to $\beta 3$ are the regression coefficients, and ε is the error term. The assumptions of linearity, independence of residuals, homoscedasticity, normality of residuals, and absence of severe multicollinearity were tested before the results were interpreted (Abulela & Harwell, 2020). Three supplementary analyses followed. First, common-method variance was assessed with Harman's single-factor test, a comparison of the four-factor CFA with a single-factor model, and the correlational marker technique, which uses the smallest inter-construct correlation as a conservative estimate of method variance (Lindell & Whitney, 2001; Podsakoff et al., 2003).

Second, to test whether perceived usefulness relates to operational efficiency indirectly, a parallel mediation model was estimated with perceived usefulness as the predictor, perceived ease of use and actual system usage as mediators, and operational efficiency as the outcome. The model was estimated by ordinary least squares following the specification of PROCESS Model 4, and the significance of the indirect effects was assessed with 95% percentile bootstrap confidence intervals based on 5,000 resamples (Hayes, 2018). This mediation analysis was exploratory and was not part of the original hypotheses. Third, because the senior and ICT groups were small, differences in construct scores across occupational levels were examined with the Kruskal–Wallis test.

RESULTS

Respondent profile

Table 2 summarizes the profile of the 89 respondents. The sample was broadly balanced by gender, predominantly mid-career, highly educated, and experienced, with more than half having worked at NIC for at least five years. The respondents were therefore well placed to assess NIC's IT systems on the basis of substantial first-hand use.

Table 2: Respondent profile (n = 89)

Characteristic	Category	Frequency	Percent (%)
Gender	Male	49	55.1
	Female	40	44.9
Age (years)	18–27	17	19.1
	28–37	41	46.1
	38–47	23	25.8
	48 and above	8	9.0
Education	Diploma	6	6.7
	Bachelor's degree	69	77.5
	Master's degree	14	15.7
Experience at NIC	Less than 1 year	11	12.4
	1–5 years	31	34.8
	5–10 years	28	31.5
	10 years or more	19	21.3

Source: Field data (2024). No respondent held a certificate or doctoral degree as the highest qualification.

Descriptive statistics

Table 3 reports item-level means, standard deviations, and the percentage of respondents who agreed or strongly agreed with each statement. Ratings were favorable across all four constructs. Actual system usage recorded the highest construct mean (M = 4.38), followed by perceived ease of use (M = 4.28) and perceived usefulness (M = 4.18); operational efficiency averaged 4.30. Every item attracted at least 80% agreement, indicating that NIC staff hold consistently positive views of the corporation's IT systems and of their effect on operational outcomes.

Table 3: Descriptive statistics of measurement items

Construct and item	Mean	SD	Agree (%)
Perceived usefulness (PU)	**4.18**		
PU1: IT improves the organization's productivity	4.19	0.96	88.8
PU2: IT improves communication and collaboration	4.20	0.77	86.5
PU3: IT facilitates timely access to information for decision-making	4.12	0.91	82.0
PU4: IT increases the quality of services provided	4.18	0.83	85.4

PU5: IT contributes to achieving organizational goals	4.20	0.93	85.4
Perceived ease of use (PEOU)	**4.28**		
PEOU1: Simplifying IT systems would improve task efficiency	4.51	0.83	94.4
PEOU2: Training adequately prepares employees to use IT systems	4.20	0.84	87.6
PEOU3: System design and interface are easy to navigate	4.12	0.80	80.9
PEOU4: Technical support is prompt and helpful	4.21	0.83	84.3
PEOU5: Prior experience and skills influence ease of use	4.36	0.74	92.1
Actual system usage (ASU)	**4.38**		
ASU1: IT streamlines processes better than manual methods	4.47	0.85	92.1
ASU2: IT is integral to job performance	4.40	0.73	95.5
ASU3: The organization encourages effective IT use	4.37	0.76	91.0
ASU4: System performance and reliability are satisfactory	4.20	0.73	84.3
ASU5: The organization benefits from effective IT use	4.43	0.77	94.4
Operational efficiency (OE)	**4.30**		
OE1: IT has improved underwriting efficiency	4.43	0.67	94.4
OE2: IT has expedited claims processing	4.36	0.64	93.3
OE3: IT enhances the accuracy of actuarial calculations	4.20	0.81	84.3
OE4: IT simplifies policy document management	4.31	0.70	88.8
OE5: IT enhances risk identification and assessment	4.20	0.79	82.0

Source: Field data (2024). Agree (%) combines "agree" and "strongly agree". Construct means are the means of the item means.

Reliability and construct validity

As shown in Table 4, Cronbach's alpha ranged from .758 to .823, exceeding the .70 threshold for all four constructs and indicating acceptable internal consistency. The PCA of the three IT construct scores was supported by a Kaiser-Meyer-Olkin value of .697 and a significant Bartlett's test of sphericity, $\chi^2(3) = 122.43$, $p < .001$. A single component with an eigenvalue of 2.310 was extracted, explaining 77.0% of the variance, with loadings of .818 to .908 and communalities of .670 to .824. This indicates that the three IT constructs, although theoretically distinct, share substantial common variance in this sample, a pattern that is important for interpreting the regression results and is examined further below.

Table 4: Reliability and principal components results

Construct	Items	Cronbach's alpha	Communality	Component loading
Perceived usefulness	5	.798	.670	.818
Perceived ease of use	5	.758	.824	.908
Actual system usage	5	.818	.817	.904
Operational efficiency	5	.823	—	—

Source: Field data (2024). KMO = .697; Bartlett's $\chi^2(3) = 122.43$, $p < .001$; one component extracted (eigenvalue = 2.310; 77.0% of variance).

The four-factor CFA showed that all 20 items loaded significantly on their intended constructs ($p < .001$), with standardized loadings from .413 to .832 (Table 5). Seventeen of the 20 loadings exceeded .55; the weakest item was PU2 (communication and collaboration, .413). Composite reliability ranged from .756 to .827, supporting internal consistency, but AVE ranged from .384 to .495, slightly below the .50 benchmark for all four constructs, so convergent validity was only partly supported. Model fit was below conventional standards, $\chi^2(164) = 313.19$, $p < .001$, $\chi^2/df = 1.91$, CFI = .817, TLI = .789, RMSEA = .102, SRMR = .092 (Hu & Bentler, 1999). Modest fit is common when a 20-item model is estimated on fewer than 100 cases, but together with the AVE values, it indicates that the scales would benefit from refinement. The full item set was retained because deleting items after the fact would have changed the scales used in the main analysis.

Table 5: Confirmatory factor analysis: standardized loadings, composite reliability, and average variance extracted

Construct	Item 1	Item 2	Item 3	Item 4	Item 5	CR	AVE
Perceived usefulness	.782	.413	.711	.621	.811	.807	.466
Perceived ease of use	.684	.598	.582	.665	.561	.756	.384
Actual system usage	.694	.832	.631	.584	.739	.827	.492
Operational efficiency	.544	.618	.820	.748	.751	.827	.495

Source: Field data (2024). Four-factor CFA estimated by maximum likelihood, n = 89; all loadings $p < .001$. Items are numbered as in Table 3. $\chi^2(164) = 313.19$; CFI = .817; TLI = .789; RMSEA = .102; SRMR = .092. CR = composite reliability; AVE = average variance extracted.

Correlations and discriminant validity

Table 6 reports the correlations among the four constructs below the diagonal and the HTMT ratios above it. All three IT constructs were positively and significantly correlated with operational efficiency. Following Cohen (2013), perceived ease of use ($r = .604$) and actual system usage ($r = .571$) were strongly correlated with operational efficiency, while perceived usefulness showed a moderate correlation ($r = .335$). The HTMT ratios involving perceived usefulness (.427 to .772) and those between operational efficiency and the other constructs (.427 to .768) were below .85, supporting discriminant validity for these pairs. The HTMT ratio between perceived ease of use and actual system usage, however, was .987, well above the .90 threshold, and their latent correlation in the CFA was .974. Because the AVE of perceived ease of use was low (.384), its latent correlations with perceived usefulness (.730) and operational efficiency (.718) also exceeded the square root of its AVE (.620), so the stricter Fornell–Larcker criterion was not met for this construct.

Consistent with these results, a three-factor model in which the ease-of-use and usage items loaded on a single factor fitted no worse than the four-factor model, $\Delta\chi^2(3) = 2.76$, $p = .430$. In this sample, therefore, perceived ease of use and actual system usage could not be clearly distinguished empirically, and their separate effects in the regression model should be interpreted with caution; they are better read together as indicating systems that are both usable and routinely used.

Table 6: Construct correlations and discriminant validity

Construct	PU	PEOU	ASU	OE
Perceived usefulness (PU)	(.683)	.772	.726	.427
Perceived ease of use (PEOU)	.597**	(.620)	.987	.768
Actual system usage (ASU)	.587**	.775**	(.701)	.704
Operational efficiency (OE)	.335**	.604**	.571**	(.703)

Source: Field data (2024). Pearson correlations of construct scores are below the diagonal; HTMT ratios are above the diagonal; the square root of the AVE is on the diagonal in parentheses. ** $p < .01$ (2-tailed), n = 89.

Regression analysis and diagnostics

The diagnostic tests supported the use of multiple linear regression. A scatterplot of operational efficiency against the IT constructs showed a broadly linear pattern. The Durbin-Watson statistic of 2.014 indicated independence of residuals, and the plot of standardized residuals against predicted values showed no funnel pattern, supporting homoscedasticity. Residuals were normally distributed, Kolmogorov-Smirnov = .051, p = .200, and Shapiro-Wilk = .989, p = .684, as also shown by the normal P-P plot in Figure 2. Tolerance values (.369 to .605) and variance inflation factors (1.653 to 2.713) were within conventional limits, indicating no severe multicollinearity, although the VIFs confirm meaningful shared variance among the predictors.

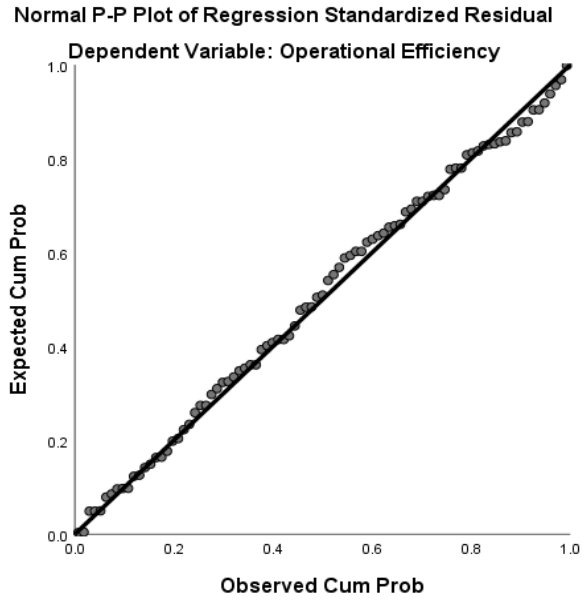

Figure 2: Normal P-P plot of standardized residuals

The regression model was statistically significant, $F(3, 85) = 18.60$, $p < .001$, and the three constructs jointly explained 39.6% of the variance in operational efficiency ($R^2 = .396$; adjusted $R^2 = .375$). Table 7 presents the coefficients.

Table 7: Multiple regression results for operational efficiency

Predictor	B	SE	β	t	p	Tolerance	VIF
(Constant)	1.636	0.383	—	4.276	< .001	—	—
Perceived usefulness	−0.081	0.091	−.096	−0.881	.381	.605	1.653
Perceived ease of use	0.423	0.134	.438	3.156	.002	.369	2.713
Actual system usage	0.273	0.131	.287	2.087	.040	.375	2.665

Source: Field data (2024). Dependent variable: operational efficiency. $R = .630$; $R^2 = .396$; adjusted $R^2 = .375$; SE of estimate = 0.440; $F(3, 85) = 18.60$, $p < .001$; Durbin-Watson = 2.014. B = unstandardized coefficient; β = standardized coefficient.

The fitted model is:

$$OE = 1.636 - 0.081PU + 0.423PEOU + 0.273ASU$$

Perceived ease of use was the strongest independent predictor of operational efficiency: holding the other constructs constant, a one-unit increase in perceived ease of use was associated with a 0.423-unit increase in operational efficiency. Actual system usage also had a positive and significant effect, with a one-unit increase

associated with a 0.273-unit increase in operational efficiency. The coefficient for perceived usefulness was small, negative, and not statistically significant; it therefore provides no reliable evidence of an independent effect in either direction. Table 8 summarizes the hypothesis tests.

Table 8: Summary of hypothesis tests

Hypothesis	Path	B	p	Decision
H1	Perceived usefulness → Operational efficiency	−0.081	.381	Not supported
H2	Perceived ease of use → Operational efficiency	0.423	.002	Supported
H3	Actual system usage → Operational efficiency	0.273	.040	Supported

Source: Field data (2024). Decisions are based on $\alpha = .05$.

Common-method variance

Because all constructs were measured with the same self-reported instrument, common-method variance was examined in three ways. In Harman's single-factor test, the first unrotated factor of the 20 items accounted for 38.5% of the variance, below the 50% threshold, and five factors had eigenvalues above 1. A single-factor CFA fitted far worse than the four-factor model, $\Delta\chi^2(6) = 121.90$, $p < .001$ (CFI = .676; RMSEA = .133). In addition, the correlations of perceived ease of use and actual system usage with operational efficiency were re-estimated after partialing out a conservative estimate of method variance, taken as the smallest inter-construct correlation ($r = .335$) (Lindell & Whitney, 2001). Both relationships remained positive and statistically significant: perceived ease of use, adjusted $r = .405$, $t(86) = 4.10$, $p < .001$; actual system usage, adjusted $r = .355$, $t(86) = 3.52$, $p < .001$. Because the marker used here is itself a substantive construct, this adjustment is likely to over-correct, so the true relationships are probably stronger than the adjusted values. Common-method variance alone is therefore unlikely to account for the main findings, although it cannot be ruled out entirely.

Supplementary mediation analysis

Table 9 reports the parallel mediation results. Perceived usefulness was positively associated with both perceived ease of use ($a1 = 0.523$, $p < .001$) and actual system usage ($a2 = 0.522$, $p < .001$). The total effect of perceived usefulness on operational efficiency was significant ($c = 0.283$, $p = .001$), whereas its direct effect after accounting for the two mediators was not ($c' = -0.081$, $p = .381$). The total indirect effect was 0.363 (completely standardized effect = .430), and its 95% bootstrap confidence interval excluded zero. The indirect effect through perceived ease of use was significant, but the indirect effect through actual system usage was not, because its confidence interval included zero. The contrast between the two indirect effects was also not significant, so neither pathway can be shown to be stronger than the other. Given the near-collinearity of the two mediators, the specific indirect effects should be interpreted with caution.

Table 9: Parallel mediation of the perceived usefulness–operational efficiency relationship

Effect	Path	Estimate (B)	SE	95% bootstrap CI
Indirect effect 1	PU → PEOU → OE	0.221	0.093	[0.046, 0.409]
Indirect effect 2	PU → ASU → OE	0.142	0.098	[−0.038, 0.343]
Total indirect effect	PU → PEOU and ASU → OE	0.363	0.111	[0.116, 0.552]
Contrast	Indirect 1 − Indirect 2	0.078	0.156	[−0.221, 0.406]
Direct effect (c′)	PU → OE	−0.081	0.091	p = .381
Total effect (c)	PU → OE	0.283	0.085	p = .001

Source: Field data (2024). Unstandardized estimates from a parallel mediation model following PROCESS Model 4 (Hayes, 2018); SEs for indirect effects are bootstrap SEs, and confidence intervals are percentile

intervals based on 5,000 bootstrap resamples. The analysis is exploratory and cross-sectional.

Perceptions across occupational levels

Mean construct scores were similar across occupational levels. Kruskal–Wallis tests found no significant differences between senior staff (directors, heads of unit, and section managers; n = 10), ICT officers (n = 11), and general users (n = 68) in perceived usefulness, $H(2) = 0.06$, $p = .971$; perceived ease of use, $H(2) = 1.86$, $p = .394$; actual system usage, $H(2) = 0.46$, $p = .796$; or operational efficiency, $H(2) = 3.54$, $p = .170$. Senior staff rated operational efficiency somewhat higher ($M = 4.58$) than general users ($M = 4.25$), but with groups this small the tests have little power, so the absence of significant differences should not be taken as evidence that hierarchy has no effect.

DISCUSSION

Perceived usefulness

The absence of an independent effect of perceived usefulness must be reconciled with two other results from the same data: more than 82% of respondents agreed with every usefulness item (Table 3), and perceived usefulness was positively and significantly correlated with operational efficiency ($r = .335$). The supplementary mediation analysis offers a consistent explanation. Perceived usefulness was associated with operational efficiency indirectly (total indirect effect = 0.363), mainly through its association with ease of use (0.221, 95% CI [0.046, 0.409]); the path through system usage was positive but not significant. Its direct effect was negligible once those constructs were taken into account. Employees who rate IT as useful are largely the same employees who find it easy to use and report using it extensively.

This pattern is consistent with TAM's own causal structure, in which perceived usefulness is expected to act on outcomes indirectly through attitude, intention, and usage rather than directly on performance (Davis, 1989; Venkatesh et al., 2003). Wang et al. (2019) reported a comparable pattern for mobile health insurance in Indonesia, where the direct effect of usefulness on intention disappeared once attitude entered the model. The result contrasts with Naicker and Van Der Merwe (2018), Gharakhani and Pourhashemi (2020), and Pham et al. (2022), who each found significant direct effects of usefulness. A plausible reason is that those studies modeled usefulness against behavioral intention, an outcome that sits close to usefulness in TAM's causal chain, whereas the present study modeled it against a downstream measure of organizational performance. Two cautions apply. Mediation estimated from cross-sectional data shows a pattern of association that is consistent with an indirect pathway but cannot establish the temporal ordering that a causal mediation claim requires (Maxwell & Cole, 2007). The result should therefore be read as supporting, not proving, the indirect role of usefulness. The practical implication is not that NIC staff fail to see value in IT, since they clearly do, but that perceived value appears to translate into efficiency through usable systems that are actually used.

Perceived ease of use

Perceived ease of use emerged as the strongest predictor of operational efficiency in the regression model, consistent with Toukabri and Ettis (2021), Huang et al. (2019), and Pham et al. (2022). Ease of use appears to work by lowering the cost of engagement: when systems are intuitive, employees spend less time on navigation and troubleshooting and more time on substantive underwriting, claims, and actuarial work. The item-level results reinforce this interpretation.

Although most respondents found NIC's interfaces easy to navigate, this item recorded the lowest agreement within the construct (80.9%), while 94.4% agreed that simplifying IT systems would improve task efficiency. Interface simplification, accompanied by ongoing training and responsive technical support, is therefore where NIC is most likely to find further efficiency gains.

Actual system usage

Actual system usage also had a positive and significant effect, consistent with Hammouri et al. (2021), Wang

et al. (2019), and Habeeb et al. (2021). Whereas usefulness and ease of use describe perceptions, actual usage describes behavior, and it is behavior that ultimately determines whether IT is put to work in core insurance functions. This agrees with Nsour et al. (2023), Moyo et al. (2022), and Kaur and Singh (2023), who argue that what holds insurance technology back is less whether systems exist than whether people actually use them. It also aligns with Köhne and Köhne (2024) and Eckert et al. (2022) on the functions, such as underwriting speed, claims turnaround, and risk assessment, in which well-adopted digital systems deliver measurable gains. Given the very high HTMT ratio between ease of use and usage, however, the two findings are best interpreted together: systems that staff find easy to use are also the systems they use routinely, and it is this combination that is associated with operational efficiency at NIC. The usage finding is also the less robust of the two: its effect was smaller and only just significant, and the indirect path from usefulness through usage was not significant in the bootstrap analysis.

Theoretical and practical implications

Theoretically, the study provides partial support for TAM. It confirms the central roles of ease of use and actual usage in realized technology benefits, while suggesting that the role of perceived usefulness becomes largely indirect when the outcome is organizational performance rather than behavioral intention. This possible boundary condition suggests that TAM applications concerned with performance outcomes should treat usefulness as working through usability and use, not as an independent driver. The study also extends TAM to an under-researched African insurance context and to a function-level measure of operational efficiency.

Practically, the findings indicate that NIC and comparable insurers should put their IT spending into usability and adoption. Adding system features, or running campaigns to persuade staff that IT is useful, is unlikely to help much, because staff already believe it. Specific actions include simplifying interfaces on the basis of structured user feedback, replacing one-off sessions with continuous training, maintaining a responsive technical support function, and embedding expectations of system use in operational policy and performance review. For regulators such as TIRA, the results suggest that digitization initiatives are more likely to improve service outcomes, including claims settlement times, when they are accompanied by support for user capability and system usability.

Limitations and directions for future research

The study has several limitations. First, it was confined to a single organization, which limits generalization to other insurers with different systems, staff profiles, or levels of IT maturity. Second, its cross-sectional design captures associations at one point in time; it cannot establish causality, and the mediation results in particular describe a pattern consistent with, but not proof of, an indirect pathway. Third, all constructs were measured through a single self-reported questionnaire, which exposes the results to common-method variance and social desirability bias. Procedural safeguards, Harman's test, the single-factor CFA comparison, and the marker-variable sensitivity check suggest that these biases do not explain the main findings, but they cannot be excluded. Fourth, general users made up 76.4% of the sample, and senior staff only 10 respondents. Although this mirrors the composition of the headquarters workforce, the findings mainly reflect the views of operational staff. Managers, who are more involved in IT investment decisions, may judge system usefulness and efficiency differently, and the small number of senior respondents limits comparison across hierarchical levels; the Kruskal–Wallis tests found no significant differences, but they had little power to detect them. Fifth, although the item-level CFA supported composite reliability, the AVE values were slightly below .50, the model's fit was below conventional standards, and perceived ease of use and actual system usage were not empirically distinct. Future research should therefore use multi-firm and longitudinal designs, collect outcome data from a separate source such as objective claims turnaround times, sample enough senior staff to compare perceptions across hierarchical levels, refine the ease-of-use and usage scales so that the two constructs can be separated, and test the indirect pathway from usefulness to performance with full structural equation modeling in larger samples.

CONCLUSION

This study examined the effect of perceived usefulness, perceived ease of use, and actual system usage of IT on operational efficiency at the National Insurance Corporation of Tanzania. Perceived ease of use and actual system usage had positive and significant independent effects on operational efficiency, whereas perceived usefulness had no significant independent effect once the other two constructs were controlled for. An exploratory mediation analysis indicated that perceived usefulness was associated with operational efficiency indirectly, mainly through ease of use. At NIC, operational efficiency is associated with IT systems that are easy to use and actually used; employees' general belief that IT is useful does not appear to be enough on its own. These conclusions should be read in light of the limitations discussed above, particularly the cross-sectional, single-source design and the overlap between ease of use and system usage.

ETHICAL CONSIDERATIONS

Research clearance was granted by the Tanzania Institute of Accountancy (Ref. No. BE.30/390/01/40, 29 May 2024), and the National Insurance Corporation of Tanzania approved data collection at its headquarters for the period April to October 2024 (Ref. No. HA.28/463/01/11). Participation was voluntary, informed consent was obtained from all respondents, and responses were anonymized at the point of collection.

CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the author upon reasonable request. The data are not publicly available because they contain information that could compromise the confidentiality of participating employees.

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REFERENCES

1. Abulela, M. A. A., & Harwell, M. M. (2020). Data analysis: Strengthening inferences in quantitative education studies conducted by novice researchers. Educational Sciences: Theory and Practice, 20(1), 59–78. https://doi.org/10.12738/jestp.2020.1.005
2. Agarwal, S., Bhardwaj, G., Saraswat, E., Singh, N., Aggarwal, R., & Bansal, A. (2022). Insurtech fostering automated insurance process using deep learning approach. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (pp. 386–392). IEEE. https://doi.org/10.1109/ICIPTM54933.2022.9753891
3. Ajibade, P. (2018). Technology acceptance model limitations and criticisms: Exploring the practical applications and use in technology-related studies, mixed-method, and qualitative research. Library Philosophy and Practice (e-Journal), 1941. https://digitalcommons.unl.edu/libphilprac/1941
4. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
5. Borgstede, M., & Scholz, M. (2021). Quantitative and qualitative approaches to generalization and replication – A representationalist view. Frontiers in Psychology, 12, Article 605191. https://doi.org/10.3389/fpsyg.2021.605191

6. Bothma, M., & Mostert, L. (2023). Adopting the technology acceptance model: A Namibian perspective. SA Journal of Information Management, 25(1), Article a1624. https://doi.org/10.4102/sajim.v25i1.1624
7. Cohen, J. (2013). Statistical power analysis for the behavioral sciences. Routledge. https://doi.org/10.4324/9780203771587
8. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297–334. https://doi.org/10.1007/BF02310555
9. Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results [Doctoral dissertation, Massachusetts Institute of Technology]. MIT Sloan School of Management.
10. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
11. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. Management Science, 35(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982
12. de Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Explaining policyholders' chatbot acceptance with an unified technology acceptance and use of technology-based model. Journal of Theoretical and Applied Electronic Commerce Research, 18(3), 1217–1237. https://doi.org/10.3390/jtaer18030062
13. Du, S., Hashim, N., & Kamarudin, S. (2024). Unveiling the technology acceptance model: A systematic review of evolution, impact across industries and future directions. Pakistan Journal of Life and Social Sciences, 22(1), 1220–1240. https://doi.org/10.57239/PJLSS-2024-22.1.0083
14. Eckert, C., Neunsinger, C., & Osterrieder, K. (2022). Managing customer satisfaction: Digital applications for insurance companies. The Geneva Papers on Risk and Insurance – Issues and Practice, 47(3), 569–602. https://doi.org/10.1057/s41288-021-00257-z
15. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
16. Gharakhani, M., & Pourhashemi, S. O. (2020). Adoption of mobile insurance technology using TAM: A case study. International Journal of Industrial Engineering & Management Science, 8(2).
17. Habeeb, L. M., Khadem, E. N., & AL-Hamzawi, A. A. R. (2021). The role of information technology in developing options related to improving the productivity of the Iraqi insurance company. Academy of Strategic Management Journal, 20, 1–10.
18. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.
19. Hammouri, Q. M., Abu-Shanab, E. A., & Nusairat, N. M. (2021). Attitudes toward implementing e-government in health insurance administration. International Journal of Electronic Government Research, 17(2), 1–18. https://doi.org/10.4018/IJEGR.2021040101
20. Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (2nd ed.). Guilford Press.
21. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
22. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118
23. Huang, W. S., Chang, C. T., & Sia, W. Y. (2019). An empirical study on the consumers' willingness to insure online. Polish Journal of Management Studies, 20(1), 202–212. https://doi.org/10.17512/pjms.2019.20.1.18
24. IBM. (2023). Cost of a data breach report 2023. IBM Corporation. https://www.ibm.com/reports/data-breach
25. Igolkina, A. A., & Meshcheryakov, G. (2020). semopy: A Python package for structural equation modeling. Structural Equation Modeling: A Multidisciplinary Journal, 27(6), 952–963. https://doi.org/10.1080/10705511.2019.1704289
26. Kanapathipillai, K., Bakar, N. S. B. A., Bakhari, N. A. B. M., & Roslee, F. A. B. M. (2024). The digital shift: Evolving insurance landscape and consumer-centric digitalisation at Etiqa Insurance, Kuala

Lumpur, Malaysia. European Journal of Management and Marketing Studies, 9(2), 64–95. https://doi.org/10.46827/ejmms.v9i2.1806

27. Kaur, P., & Singh, M. (2023). Exploring the impact of InsurTech adoption in Indian life insurance industry: A customer satisfaction perspective. The TQM Journal. Advance online publication. https://doi.org/10.1108/TQM-06-2023-0186
28. Köhne, T., & Köhne, M. (2024). Uncovering the impact of digitalization on the performance of insurance distribution. Risks, 12(8), Article 129. https://doi.org/10.3390/risks12080129
29. Krishnakanthan, K., Lansing, J., Münstermann, B., Olesen, P. B., & Vogelgesang, U. (2019). Insurance IT modernization: Three paths ahead. McKinsey & Company. https://www.mckinsey.com/industries/financial-services/our-insights/it-modernization-in-insurance-three-paths-to-transformation
30. Likert, R. (1932). A technique for the measurement of attitudes. Archives of Psychology, 22(140), 1–55.
31. Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. Journal of Applied Psychology, 86(1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114
32. Malit, A., & Muendo, D. D. (2017). The effect of information communication technology strategy implementation on organizational performance of insurance sector in Kenya. The Strategic Journal of Business & Change Management, 4(2), 1–22.
33. Marikyan, D., & Papagiannidis, S. (2023). Technology acceptance model: A review. In S. Papagiannidis (Ed.), TheoryHub book. Newcastle University. https://open.ncl.ac.uk
34. Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. Psychological Methods, 12(1), 23–44. https://doi.org/10.1037/1082-989X.12.1.23
35. Mondego, D., & Gide, E. (2022). The use of the technology acceptance model to analyse the cloud-based payment systems: A comprehensive review of the literature. Journal of Information Systems and Technology Management, 19, Article e202219007. https://doi.org/10.4301/S1807-1775202219007
36. Moyo, J., Watyoka, N., & Chari, F. (2022). Challenges in the adoption of artificial intelligence and machine learning in Zimbabwe's insurance industry. In 2022 1st Zimbabwe Conference of Information and Communication Technologies (ZCICT) (pp. 1–6). IEEE. https://doi.org/10.1109/ZCICT55726.2022.10045910
37. Mueni, F., & Angima, C. (2022). Effects of digital adoption on performance of insurance companies in Kenya. International Journal of Research and Innovation in Social Science, 6(12), 614–618.
38. Naicker, V., & Van Der Merwe, D. B. (2018). Managers' perception of mobile technology adoption in the life insurance industry. Information Technology & People, 31(2), 507–526. https://doi.org/10.1108/ITP-09-2016-0212
39. Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. Advances in Health Sciences Education, 15(5), 625–632. https://doi.org/10.1007/s10459-010-9222-y
40. Nsour, M. F., AL-Rjoub, S. A. M., Tayeh, M., & Kokash, H. (2023). Factors and issues affecting electronic insurance adoption in an emerging market. Insurance Markets and Companies, 14(1), 46–58. https://doi.org/10.21511/ins.14(1).2023.05
41. Osman Opoku, M., & Enu-Kwesi, F. (2020). Relevance of the technology acceptance model (TAM) in information management research: A review of selected empirical evidence. Research Journal of Business and Management, 7(1), 34–44. https://doi.org/10.17261/Pressacademia.2020.1186
42. Parsons, V. L. (2017). Stratified sampling. In Wiley StatsRef: Statistics Reference Online (pp. 1–11). John Wiley & Sons. https://doi.org/10.1002/9781118445112.stat05999.pub2
43. Pham, Q. T., Nguyen, H. N. D., Misra, S., & Misra, A. (2022). Investigating factors for using insurance apps by customers: A study of a developing country. Journal of Banking and Financial Technology, 6(2), 149–157. https://doi.org/10.1007/s42786-022-00046-9
44. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
45. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
46. Sabu, C. M. (2023). Impact of technology on insurance industry. Journal of Emerging Technologies and Innovative Research, 10(2).

47. Saunders, M. N. K., Lewis, P., & Thornhill, A. (2023). Research methods for business students (9th ed.). Pearson Education.
48. Schuetze, L., Srivastava, S., Kuunibe, N., Rwezaula, E. J., Missenye, A., Stoermer, M., & De Allegri, M. (2023). What factors explain low adoption of digital technologies for health financing in an insurance setting? Novel evidence from a quantitative panel study on IMIS in Tanzania. International Journal of Health Policy and Management, 12(1), 1–9. https://doi.org/10.34172/ijhpm.2023.6896
49. Sibindi, A. B. (2022). Information and communication technology adoption and life insurance market development: Evidence from sub-Saharan Africa. Journal of Risk and Financial Management, 15(12), Article 568. https://doi.org/10.3390/jrfm15120568
50. Slack, N., & Brandon-Jones, A. (2019). Operations management (9th ed.). Pearson Education.
51. Taherdoost, H. (2022). What are different research approaches? Comprehensive review of qualitative, quantitative, and mixed method research, their applications, types, and limitations. Journal of Management Science & Engineering Research, 5(1), 53–63. https://doi.org/10.30564/jmser.v5i1.4538
52. Tang, M.-H., & Niu, Y.-L. (2023). Importance-performance analysis of online insurance: Communication and networking. Engineering Proceedings, 38(1), Article 7. https://doi.org/10.3390/engproc2023038007
53. Tanzania Insurance Regulatory Authority. (2022). Annual insurance market performance report. https://www.tira.go.tz
54. Tanzania Insurance Regulatory Authority. (2024). Annual insurance market performance report for the year ended 31st December 2023. https://www.tira.go.tz
55. Toukabri, M. T., & Ettis, S. A. (2021). The acceptance and behavior towards e-insurance. International Journal of E-Business Research, 17(2), 1–16. https://doi.org/10.4018/IJEBR.2021040102
56. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
57. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(5), 328–376. https://doi.org/10.17705/1jais.00428
58. Wang, G., Alatas, S., & Wiraniagara, A. (2019). Factors affecting acceptance of mobile health insurance in Indonesia: TAM applicability. International Journal of Advanced Trends in Computer Science and Engineering, 8(6), 3004–3011. https://doi.org/10.30534/ijatcse/2019/54862019
59. Wanjohi, N., & Waithaka, S. (2024). Information systems and performance of insurance firms in Nairobi County, Kenya. International Journal of Technology and Systems, 9(2), 1–20. https://doi.org/10.47604/ijts.2658
60. Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper & Row.