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Innovation Adoption, Value Recognition, and Customer Value Creation in Tanzania's Public Healthcare System. The Mediating Effects of Continuous Learning

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Abstract

This research investigates the influence of Innovation Adoption Value Recognition on customer value creation in Tanzania's public healthcare system, with continuous learning acting as a mediating factor. Using a cross-sectional design, the study collected data from 320 healthcare professionals and analysed the data using structural equation modelling. The findings indicate that the innovation adoption value recognition has a direct but minor influence on healthcare customer value creation and a statistically significant, positive impact on continuous learning. Continuous learning, in turn, serves as a major mediator of the relationship between innovation adoption, value recognition, and the resulting value, as it shows a statistically significant influence on healthcare customer value creation. The measurement model possesses high reliability and validity. However, the explanatory power is moderate for the outcome variable and limited for the mediating variable, while at the indicator level, the predictive power is weak. The results of this study highlight the need to combine innovation, recognition of the value of adoption, and continuous learning to enhance operational research and healthcare outcomes, especially in resource-limited settings. Therefore, the research suggests the use of adaptive operations research methodologies that foster the adoption of innovation, value recognition, and continuous learning in public healthcare systems. It also points out the importance of operations research for simulation, resource allocation, and decision support in such environments. The limitations are reliance on structured questionnaires and a cross-sectional design, which warrant the use of longitudinal or mixed-methods designs in future studies.

Keywords: Innovation Adoption Value Recognition; Continuous Learning; Healthcare Value Creation; Operations Research; Public Healthcare System

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Introduction

Access to healthcare services in Tanzania's public healthcare system is a matter of health policy shaped by various factors, including sustained political will. The system has, nevertheless, made considerable strides in delivering basic services, while still experiencing inefficiencies at the primary level, unresponsiveness, and the continued use of outdated service-delivery models. Among the barriers to healthcare resource development is the limited attention given to promoting innovation in healthcare customer value creation. Consequently, good health and well-being are not being made accessible in an equitable and timely manner; primary and reproductive healthcare are not up to the expected standard; and, thus, government healthcare and even global health indicators remain largely unmet (Ministry of Health, Community Development, Gender, Elderly and Children, 2021; World Health Organization [WHO], 2023). The determinants of healthcare demand, including the emergence of non-communicable diseases, demand the strategic application of healthcare and public healthcare transformation to make the public healthcare system sustainable (Mboera et al., 2018).

The process of adopting innovation and recognising its usefulness leads to a change in how healthcare customer value (HCVC) is created and delivered, especially strengthening systems in less resource-endowed environments (Wang et al., 2024). In Tanzania, however, the movement toward this aspect is not uniform; resource constraints continue to limit efficient HCVC, and the system in place is not always supportive of innovation adoption, as reflected in the recurring political, economic, social, and technological barriers to health-technology adoption identified across Tanzanian healthcare facilities (Mwogosi & Mambile, 2025). In consequence, operational research (OR) in this context can provide evidence-based insights into the systemic and organisational factors that either encourage or impede the adoption of such innovations. OR methods, including process mapping, bottleneck analysis, and system optimisation, are effective in identifying inefficiencies, prioritising interventions, and evaluating the impact of new practices, thereby facilitating more effective HCVC within Tanzania's public healthcare system (Brailsford & Vissers, 2011; Zhang, 2018).

The concepts of Innovation Adoption Value Recognition (IAVR) and Continuous Learning (CL), related respectively to Dynamic Capabilities Theory and Organisational Learning Theory, are the theoretical foundations framing the research. IAVR is conceptualised as the independent variable in this study, representing the organisation's recognition of the value of adopted innovation. Its influence on HCVC is theorised to operate both directly and indirectly, carried through Continuous Learning (CL), which functions as the mediating mechanism. Dynamic Capabilities Theory states that organisations need to discover, develop, and deploy their resources to compete, and this must be done harmoniously in

changing environments (Teece, 2011). In the present research, IAVR resembles the "sensing" dimension of dynamic capabilities (Teece, 2007): centres of Tanzania's public healthcare system should be alert to changing needs of healthcare customers, acknowledge the value of doing things in new ways, and allocate resources adaptively. Operational research can contribute significantly by presenting data-driven options to detect changes in demand, evaluate the viability and effects of innovations, and guide resource-allocation decisions.

Meanwhile, CL is firmly aligned with Organisational Learning Theory, which treats system functioning as a process of continuous learning, knowledge diffusion, and adaptation (Argyris & Schön, 1996). CL supports the "seizing" and "transforming" dimensions of dynamic capabilities, thereby enabling the public healthcare system to use the recognised value as a basis for its adaptability and development. Well-organised training and feedback cycles, supported by institutional mechanisms, facilitate healthcare workers and leaders in learning the necessary skills and adjusting their activities to ensure the successful introduction and sustainability of innovations (Manzi et al., 2017). From this angle, operational research is involved in designing and assessing these training programmes and feedback mechanisms to ensure that learning translates into practicable improvements and transferable best practices throughout the system.

The combination of these theoretical frameworks yields a more profound understanding of the HCVC process within Tanzania's public healthcare system. The theory of Dynamic Capabilities, considering IAVR, enables the organisation to identify valuable innovations to assess and prioritise in response to environmental changes. Organisational Learning Theory, guided by CL, shows the transformation of the system through the acquisition of new knowledge, the alteration of practices, and the improvement of healthcare customers. The use of operational research across these aspects fortifies the IAVR and the commitment to CL, thereby empowering organisations to generate, provide, and retain healthcare customer value despite difficulties and resource scarcity. This research, therefore, aims to shed light on the causal relationships among IAVR, CL, and HCVC. It also seeks to model the mechanisms by which the IAVR and CL processes carry innovations through the public healthcare system. Both the individual and the organisational aspects are taken into consideration.

This research would pave the way for Operations Research (OR) and public healthcare management to capitalise on new opportunities arising from their interconnection, hence its value. The findings developed in the study could also inform healthcare organisations' innovation adoption pathways, helping identify where investment of scarce resources would be most beneficial (Kuwawenaruwa et al., 2023; Stoermer et al., 2024). Accordingly, scarce organisational resources should be directed toward investments that strengthen system adaptability, technological capability, and workforce development (Kirigi et al., 2024).

Although research has extensively covered the topics of innovations adoption, continuous learning, dynamic capabilities, and organisational learning, the interaction of these aspects with HCVC in the context of the public healthcare system constrained by limited resources has not been a promising topic of research and empirical evidence (Kirigi et al., 2024; Komulainen et al., 2023). Most of the research comes from conceptualisation studies and experiments performed in locations with plentiful resources; hence, it is not so easy to decide whether or not those findings apply to Tanzania's public healthcare system, and some of the limited resources which render it even more different from the high-resource settings where most of the studies were carried out.

This study addresses these restrictions by merging IAVR with the Dynamic Capabilities Theory and CL with the Organisational Learning Theory, and presenting a new analysis tailored to the context of Tanzania's public healthcare system's organisations. The research reveals how IAVR helps transform healthcare customers' needs into identifiable values and benefits through a structural equation modelling methodology. It depicts the organisation's acceptance of these innovations, whilst exploring the mediating processes, and ultimately generating proof for strategic resource positioning. Consequently, the research advances theoretical understanding and provides practical strategies to improve the value of public healthcare in Tanzania.

Theoretical framework

This investigation involves the integration of OLT and DCV in evaluating how IAVR and CL affect HCVC in the context of the public healthcare sector. As per Huber (1991), organizational learning consists of four phases, namely, knowledge creation, knowledge acquisition, knowledge understanding, and application of knowledge. IAVR acts as a channel through which healthcare organizations learn about innovations and adopt them for increasing efficiency (Hock-Doepgen et al., 2021). Knowledge culture (CL) forms the basis of such innovation by focusing on the continuous process of knowledge creation, knowledge dissemination, and application of the knowledge. DCV stresses the importance of developing an organization's ability in response to dynamic challenges and changing requirements (Teece, 2014). Through stimulation of such abilities, IAVR, along with a CL environment, makes it possible for healthcare organizations to combine IAVR and OR approaches effortlessly to make them beneficial for

customers (Komulainen et al., 2023). According to empirical findings, public healthcare organizations, especially the ones associated with OR and possessing a strong CL culture, demonstrate dynamism and effectiveness in terms of transforming identified innovations into customer value (Kirigi et al., 2024).

Innovation adoption value recognition and healthcare customer value creation (IAVR→HCVC)

Examining the relationship between IAVR and HCVC in public healthcare systems can help explain improvements in system performance, flexibility, and quality of patient care (Adan & Mweta, 2025; Hock-Doepgen et al., 2021). OR techniques are important for identifying relationships relevant to resource allocation and for ensuring that customer needs are addressed (Kinyenje et al., 2022; Stoermer et al., 2024). Such improvements can contribute to higher customer satisfaction and more effective healthcare practices (Kinyenje et al., 2022). Using IAVR together with OR techniques can therefore support improvements in service quality and patient experience (Hock-Doepgen et al., 2021). However, studies examining IAVR with OR support, particularly in African public healthcare systems, remain scarce. This gap leads to the research question: To what extent does IAVR, supported by OR methods, positively influence HCVC in Tanzania's public healthcare system? Accordingly, the study proposed and tested the following hypothesis:

H1: IAVR, supported by OR methods, positively influences HCVC in Tanzania's public healthcare system.

Innovation adoption value recognition and Continuous learning (IAVR→CL)

Understanding the influence of IAVR on CL requires integrating systems thinking with empirical evidence, particularly in OR projects aimed at improving healthcare-system efficiency. OR provides modelling tools, including scenario analysis and discrete-event simulation, to support decision-making and process optimisation (Zhang, 2018). These tools help healthcare professionals anticipate outcomes, identify barriers, and assess potential solutions for innovation (Adan & Mweta, 2025; Hans & Rutenge, 2024). Empirical studies also show that OR-related approaches can support learning organisations in African health systems (Hans & Rutenge, 2024; Manzi et al., 2017), while innovation adoption has been associated with improved operational performance and client satisfaction in Tanzanian and Kenyan public health facilities (Adan & Mweta, 2025; Kinyenje et al., 2022). Nonetheless, evidence on the relationship between IAVR, OR support, and CL remains limited within Tanzania's public healthcare system. The study therefore asks: To what extent does IAVR, supported by OR methods, positively influence CL in Tanzania's public healthcare system? To address this question, the study tested the following hypothesis:

H_2: IAVR, supported by OR methods, positively influences CL in Tanzania's public healthcare system.

Continuous learning and healthcare customers' value creation (CL→HCVC)

CL is increasingly viewed as important for adaptable workforce development and for fostering ongoing professional growth, innovation, and customer value creation in public healthcare systems (Yang et al., 2004). Operational research (OR) can support different forms of learning through embedded learning cycles and modelling tools, such as discrete-event simulation and system dynamics, for evaluating the effects of CL on service-delivery processes and decision-making (Adan & Mweta, 2025).

Studies show that CL can improve working environments and professional standards (Mlambo et al., 2021), but evidence linking learning processes to healthcare customer value creation through OR remains limited in Tanzania's public institutions (Manzi et al., 2017). This gap leads to the research question: To what extent does CL, supported by OR methods, positively influence HCVC in Tanzania's public healthcare system? To answer this question, the study tested the following hypothesis:

H3: CL, supported by OR methods, positively influences HCVC in Tanzania's public healthcare system.

Mediating effects of continuous learning on the relationship between innovation adoption value recognition and customer value creation (IAVR→CL→HCVC)

Public healthcare stakeholders encounter challenges due to changing operational priorities and complex dynamics (Porter, 2010; Vargo & Lusch, 2016). Emphasising a customer-centric approach and utility-oriented innovation can create a sustainable framework for stakeholder value. OR models such as system dynamics and discrete-event simulation enable measurable improvements by evaluating interventions (Adan & Mweta, 2025). Investigating the relationship among IAVR, CL, and HCVC is therefore important, yet evidence in Tanzania remains limited. The study asks: To what extent does CL mediate the relationship between IAVR and HCVC in Tanzania's public healthcare system? To address this question, the study tested the following hypothesis:

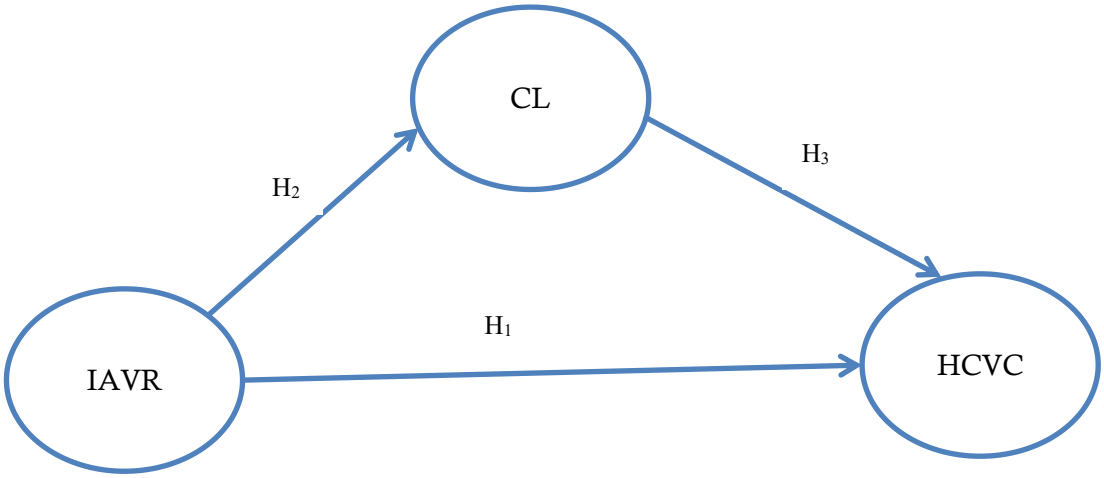
H4: CL mediates the relationship between IAVR and HCVC in Tanzania's public healthcare system.

Conceptual framework

The present study examines the hypothesised relationships among IAVR, CL, and HCVC in Tanzania's public healthcare system, with IAVR specified as the independent variable, CL as the mediating variable, and HCVC as the dependent variable. This framework aligns management interventions with healthcare value creation and changing customer needs (Porter, 2010).

Subsequently, the research aims to move beyond theoretical discovery and provide actionable recommendations to healthcare management, thereby promoting an environment in which humanity and enterprise enhance value creation and, in the process, extend knowledge of the role of organisations in the public healthcare system as learning agents. The findings underpin the arguments for public healthcare systems to significantly adopt practices focused on adaptability, flexibility, and readiness to enhance continuous performance improvement (Adan & Mweta, 2025; Haaker et al., 2021; Hans & Rutenge, 2024).

Figure 1: Conceptual Framework for the Study



Source: Developed from a synthesis of the literature reviewed (2025)

Note:
CL : Continuous Learning
HCVC : Healthcare Value Creation
IAVR : Innovation Adoption Value Recognition
H4 : Indirect mediating effect (IAVR → CL → HCVC)

Methodology

Study design

This study adopted a cross-sectional survey research design that is quite appropriate in any healthcare research since it provides the views of the population at one particular moment in time. The design is positivist, thus, making it possible to analyse many variables at once. This helps to make the identification of patterns easier and using different statistical techniques to come up with reliable conclusions. Besides, it helps generalise the results to a wider population, making it applicable to any public healthcare system study (Saunders et al., 2012).

Study area and units of analysis

The selected subjects for this study include the public zonal referral hospitals in the cities of Mbeya, Kilimanjaro, and Mwanza, in Tanzania, emphasizing the importance of these hospitals in providing specialized care, education, and clinical training to the smaller facilities (WHO, 2004). The hospitals were selected due to their important contribution to the health sector in Tanzania, as well as the consistency of their activities with the health policies and adherence to strict scientific standards (Brailsford et al., 2009; Saunders et al., 2012). Given that the selected institutions have been operating for over three decades and act as the change agents in their respective referral catchment zones, they have proven to be appropriate for further analysis, thus leading to the exclusion of others.

Population

The healthcare workers at the zonal referral hospitals in Tanzania were the main target population of this research. The members of the population were crucial to service provision in the selected zonal referral hospitals, as they were the recipients of those services. In the three chosen zonal referral hospitals, the population size available during the research period was 1,887.

Sampling Frame, Units of Inquiry, Sample Size, and Selection

The study focused on selecting employees working in selected medical departments including cardiologists, obstetricians, and dermatologists since the study aims to collect information that is relevant to the medical doctors and practitioners engaged in the HCVC process. The departments selected were meant to ensure that the research remains relevant in relation to its objectives, and this was done by following a sampling hierarchy that ensures reliability of the information gathered (Brailsford et al., 2023; Tortorella et al., 2020; Wu et al., 2025). The Krejcie and Morgan table was used to calculate a sample size of 320 from a population of 1,887 in order to make sure that the results will be statistically significant (Krejcie & Morgan, 1970). The sampling process followed a multi-stage sampling design where the sample was selected at the national level all the way to departmental level using stratified cluster sampling, followed by simple random sampling from the clusters by using the computer generated selections.

Operationalisation of the study constructs

The study constructs were operationalised from the reviewed literature. Three constructs were measured: Continuous Learning (CL), Innovation Adoption Value Recognition (IAVR), and Healthcare Value Creation (HCVC). Table 1 presents the construct definitions, the initial number of items, and pilot-study reliability assessed using Cronbach's alpha.

Table 1: Operationalisation of Constructs

Construct	Definition	No. of Items	Cronbach's Alpha
CL (Continuous Learning)	The extent to which individuals and organisations consistently engage in, and benefit from, ongoing learning activities to improve knowledge, skills, and competencies.	5	0.87
IAVR (Innovation Adoption Value Recognition)	The degree to which the adoption of new ideas, processes, or technologies is acknowledged and realised as beneficial within the organisation.	6	0.91
HCVC (Healthcare Value Creation)	The process by which healthcare organisations generate value through improved patient outcomes, service quality, and operational efficiency via human capital and innovation.	7	0.89

Note. Item pools were adapted to the public healthcare context from established scales: CL from Yang et al. (2004); IAVR from Clauss (2017); HCVC from Komulainen et al. (2023). Definitions were synthesised from the reviewed literature. Cronbach's alpha values are pilot-study estimates (Field Data, 2024).

Preparation and piloting data collection tools

An 18-item questionnaire was developed to measure the three study constructs using a 5-point Likert scale: five CL items, six IAVR items, and seven HCVC items, as reported in Table 1. The initial item pool was informed by the reviewed literature, including prior scale-development work on innovation (Clauss, 2017). The tool was piloted in public regional referral hospitals to assess reliability (Sarstedt et al., 2021). Following measurement-model assessment, the final model reported in Table 3 retained 10 indicators that met the stated criteria. Indicator loadings greater than 0.70 and Cronbach's alpha greater than 0.708 were used as measurement-model criteria (Hair et al., 2010; Sarstedt et al., 2021). For the structural model, composite reliability (rho_a and rho_c) greater than 0.70 and average variance extracted (AVE) above 0.50 were used, while discriminant validity was assessed using HTMT below 0.90 (Hair et al., 2024; Henseler et al., 2015). VIF values below 3.3 were used to assess collinearity and potential common method bias (Kock & Lynn, 2012).

Data collection

The process of data collection involved distributing 350 self-administered questionnaires through simple random sampling. The results showed that the response rate was 95.7%, with 335 responses being received. The 15 responses which had some missing information were removed from further analysis, leaving 320 actual responses. The process of data collection followed strict guidelines so as to enhance credibility of the data collected.

Data analysis

The researchers employed a quantitative descriptive approach to analyse the respondents' demographic characteristics and assess relationships among the study variables (Saunders et al., 2012). Data quality was evaluated by removing missing values, wrong entries, and outliers using IBM SPSS version 25, which is broadly recognised for its effectiveness in descriptive statistical analysis (Sarstedt et al., 2021). Subsequently, all model indicators were subjected to Partial Least Squares-Confirmatory Composite Analysis (PLS-CCA) using SMART-PLS version 4.0, a robust method for analysing complex relationships among constructs in quantitative data (Hair et al., 2010).

The inferential analysis was conducted to evaluate the measurement model by applying decision criteria, including indicator loadings > 0.7 and reliability based on Cronbach's alpha > 0.708 (Sarstedt et al., 2021). The assessment of the structural model focused on evaluating internal consistency using composite reliability (CR) thresholds of rho_a > 0.7 and rho_c > 0.7, as well as average variance extracted (AVE) > 0.5. In addition, discriminant validity was verified using the Heterotrait-Monotrait ratio (HTMT) < 0.90, with a p-value of 0.05 and a 95% confidence interval (Hair et al., 2019).

To minimise common method bias (CMB) and self-report bias, the researcher adopted several established procedures (Conway & Lance, 2010). The variance inflation factor (VIF) was used to assess multicollinearity, with a threshold of <3.3 (Kock & Lynn, 2012). The outcomes of these analyses indicated that CMB and multicollinearity were not a concern (Podsakoff et al., 2003). Collectively, these measures ensured the validity and reliability of the research findings (Conway & Lance, 2010). Also, respondents were informed that there were no right or wrong answers, and were assured of their anonymity, with the importance of providing honest and independent responses emphasised throughout. Reverse-coded indicators were integrated into the self-administered questionnaire to enhance the likelihood of identifying and minimising respondent bias, thereby fostering the reliability of the research findings (Spector, 1992). Following data collection, a marker-variable approach was used to assess potential common method variance (Lindell & Whitney, 2001).

Hypothesis testing

To test the hypothesised relationships between constructs, the study employed bootstrapping with 5,000 resamples, using $p < .05$ and $t > 1.96$ as significance criteria (Sarstedt et al., 2021). The structural model's explanatory power was assessed using the coefficient of determination (R^2) for the endogenous constructs CL and HCVC; R^2 values of 0.67 or above were treated as substantial, 0.33 to 0.67 as moderate, and 0.19 to 0.33 as weak (Sarstedt et al., 2021). Predictive relevance was assessed using Q^2predict, with positive values indicating predictive relevance; the reported indicator-level ranges were used to describe the model's predictive performance (Hair et al., 2024). Effect sizes (f^2) were interpreted as large at ≥ 0.35, medium from 0.15 to < 0.35, and small from 0.02 to < 0.15 (Sarstedt et al., 2021). Model fit was assessed using the Standardised Root Mean Square Residual (SRMR), with values below 0.08 indicating acceptable fit (Hu & Bentler, 1999).

Validity, reliability, and ethical considerations

The questionnaire was reviewed by five experts from regional referral hospitals in Dar es Salaam and refined before the main study (Saunders et al., 2012). Reliability and measurement quality were assessed using test–retest and split-half procedures, indicator loadings above 0.70, Cronbach's alpha above 0.708, composite reliability (rho_a and rho_c) above 0.70, and AVE above 0.50 (Hair et al., 2011; Sarstedt et al., 2021). Ethical approval was obtained from the University of Dar es Salaam Ethics Committee (Ref: AB3/12(B)). All respondents provided informed consent and were assured of anonymity.

Results

Descriptive analysis and implications

The final analytical sample comprised 320 respondents, of whom 55.6% were male and 44.4% were female. Most respondents were younger than 40 years, and the largest marital-status category was married. Participants represented medical experts, nurses, diagnostic scientists, pharmacists, and quality-assurance/physiotherapy staff. Approximately half reported less than five years of work experience, and respondents were distributed across the three zonal referral hospitals. These characteristics provide variation in professional background, experience, and institutional setting.

Table 2: Summary of Respondents' Demographic Characteristics (N = 320)

Characteristic	Category / Range	n (%)
Gender	Male	178 (55.6%)
	Female	142 (44.4%)
Age (years)	<29	121 (37.8%)
	30–39	126 (39.4%)
	40–49	46 (14.4%)
	≥50	27 (8.4%)
Marital Status	Single	141 (44.2%)
	Married	176 (55.2%)
	Divorced	2 (0.6%)
Profession	Medical Experts	111 (34.7%)
	Nurses	94 (29.4%)
	Diagnostic Scientists	55 (17.2%)
	Pharmacists	34 (10.6%)
	Quality Assurance/Physiotherapy	26 (8.1%)
Hospital Affiliation	Bugando Zonal Referral Hospital	115 (35.9%)
	Kilimanjaro Christian Med. Centre	103 (32.2%)
	Mbeya Zonal Referral Hospital	102 (31.9%)
Work Experience (yrs)	<5	158 (50.3%)
	5–15	117 (37.3%)
	16–25	34 (10.8%)
	>25	5 (1.6%)

Note. N = 320. Percentages are computed on the valid responses for each characteristic. Valid n = 320 for gender, age, profession and hospital affiliation; n = 319 for marital status and n = 314 for work experience, reflecting item non-response. Source: Field Data (2024).

Assessment of the measurement model

The findings of the assessment of the measurement model are presented in Table 3.

Table 3: Findings of the evaluation of the measurement model (n = 320)

Construct	Indicator	Loading	Cronbach's Alpha (α)
Thresholds		> 0.70	> 0.708
HCVC (Healthcare Value Creation)	HCVC12	0.777	0.761
	HCVC13	0.856	
	HCVC14	0.833	
CL (Continuous Learning)	CL17	0.729	0.755
	CL19	0.713	
	CL24	0.806	
	CL25	0.789	
IAVR (Innovation Adoption Value Recognition)	IAVR30	0.842	0.779
	IAVR31	0.839	
	IAVR32	0.818	

Source: Field Data (2024)

Table 3 presents the findings of the measurement model based on the sample of 320 respondents. Every indicator loading exceeded the cut-off value of 0.7, and similarly, the Cronbach's alpha for each construct exceeded the established threshold of 0.708. The findings indicate that the measurement indicators are valid and reliable, supporting the strength of the study's measurement model. Consequently, the outer structure of the model, as shown in Figure 2, is characterised by increased validity and reliability, thereby boosting confidence in the research results and the theoretical links examined (Sarstedt et al., 2021).

Structural Model Assessment

The study analysed the structural model for internal consistency, convergent validity, discriminant validity, and collinearity. Findings were within the established thresholds, supporting model reliability and validity (Sarstedt et al., 2021). Table 4 summarises internal consistency, convergent validity, collinearity, common method bias, and the reported HTMT results.

Table 4: Findings of the Assessment of Structural Model (n = 320)

Construct	rho_a	rho_c	AVE	HTMT	VIF/CMB	Remarks
IAVR	0.766	0.846	0.578	—	1.417	Acceptable
CL	0.771	0.863	0.677	—	1.000	Acceptable
HCVC	0.786	0.872	0.694	—	1.417	Acceptable
HTMT range	—	—	—	0.576–0.790	—	—

Source: Field Data (2024)

Thresholds: rho_a and rho_c > 0.70; AVE ≥ 0.50; HTMT < 0.90; VIF < 3.3 (Sarstedt et al., 2021)
The results in Table 4 show that the composite reliability values (rho_a and rho_c) for IAVR, CL, and HCVC are all above 0.70, indicating adequate internal consistency. The AVE values are all above 0.50, supporting convergent validity. VIF values are below 3.3, indicating that problematic collinearity is not evident in the reported model.

The three reported HTMT coefficients range from 0.576 to 0.790, all below the 0.90 threshold, supporting discriminant validity among the constructs. The reported VIF values are also below 3.3. Collectively, these results support the adequacy, reliability, and validity of the structural model within the reported assessment criteria.

Table 5: Explanatory and Predictive Power (n = 320)

Path/Construct	R^2	R^2 adj	f^2	Q^2predict (Range)	Remarks
CL	0.294	0.293	-	0.114 – 0.225	-
HCVC	0.390	0.387	-	0.090 – 0.185	-
IAVR -> HCVC	-	-	0.035	-	Weak
IAVR -> CL	-	-	0.417	-	Large
CL -> HCVC	-	-	0.306	-	Moderate

Source: Field Data (2024)

The structural model results in Table 5 demonstrate that the model explains 29.4% of the variance in CL and 39.0% of the variance in HCVC, indicating weak explanatory power for CL and moderate explanatory power for HCVC. IAVR-to-CL has a large effect (f^2 = 0.417), CL-to-HCVC has a medium effect (f^2 = 0.306), and the direct effect of IAVR on HCVC is small (f^2 = 0.035). The positive Q^2predict values (0.090–0.225) indicate predictive relevance, although the magnitude of predictive performance remains limited at the indicator level.

Hypothesis Testing

Table 6 presents the results of hypothesis testing, reporting the standardised path coefficients (β), t-values, p-values, and 95% confidence intervals. Findings of the hypothesis testing reveal that all hypothesised paths were statistically significant ($p < .05$, $t > 1.96$), supporting H1, H2, H3, and H4.

Table 6: Results of Hypothesis Testing and Mediation Analysis (n = 320)

Path	Hypothesis	β (O)	95% CI (LL, UL)	t-value	p-value	Supported
IAVR -> HCVC	H_1	0.173	0.037, 0.309	2.512	.012	Yes
IAVR -> CL	H_2	0.542	0.416, 0.668	8.493	<.001	Yes
CL -> HCVC	H_3	0.514	0.369, 0.659	6.958	<.001	Yes
IAVR -> CL -> HCVC	H_4	0.279	0.187, 0.371	5.991	<.001	Yes*

Source: Field Data (2024)

Key:
β (O): Standardised beta coefficient (original sample estimate)
95% CI: Bias-corrected bootstrap confidence interval (lower limit, upper limit)
*H4: Significant complementary partial mediation effect

The hypothesis tests confirm statistically significant relationships for all the hypothesised paths (H1; H2; H3 and H4), with p-values < 0.05 and t-values > 1.96. The paths' effect sizes ranged from weak (IAVR -> HCVC) to moderate (CL -> HCVC) to large (IAVR -> CL), supporting the study's theoretical explanation. These results affirm the validity and reliability of the structural model, strengthening its relevance for practitioners and policymakers in public healthcare value creation (Hair et al., 2019; Sarstedt et al., 2021).

Mediation Analysis (IAVR -> CL->HCVC)

This study explored whether CL mediates the relationship between IAVR and HCVC in Tanzania's public healthcare system, as indicated in Table 7.

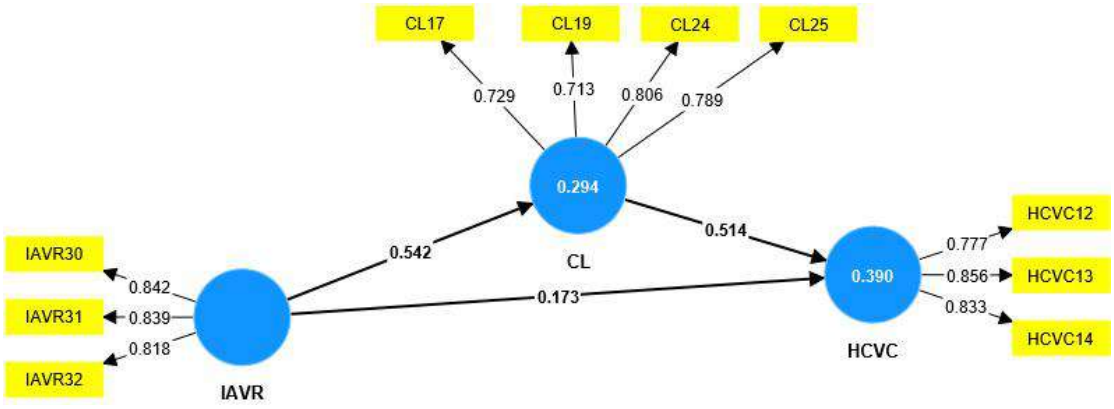
Table 7: Mediation Analysis Results for Continuous Learning (CL) as a Mediator between Innovation Adoption Value Recognition (IAVR) and Healthcare Value Creation (HCVC) (N = 320)

Effect Type	Path	Effect (β)	SE	95% CI (LL, UL)	p-value
Total Effect	IAVR → HCVC	0.451	0.065	0.322, 0.580	< .001
Direct Effect	IAVR → HCVC (controlling for CL)	0.173	0.069	0.037, 0.309	.012
Indirect Effect	IAVR → CL → HCVC	0.279	0.047	0.187, 0.371	< .001

Source: Field Data (2024)
SE = Standard Error; CI = Confidence Interval; Bootstrap method used for indirect effect.

The mediation analysis results reveal a significant total effect of IAVR on HCVC (β = 0.451, p < 0.001), indicating that IAVR has a considerable influence on HCVC when both direct and indirect pathways are considered (total effect). When controlling for CL, the direct effect of IAVR on HCVC remains significant but with a lower magnitude (β = 0.173, p = 0.012), indicating that the mediator (CL) is partially mediating the effect. The effect of IAVR on HCVC via CL is (the mediation effect) statistically significant (β = 0.279, SE = 0.047, 95% CI [0.187, 0.371], p < 0.001), because the confidence interval does not cover zero. This series of findings establishes the presence of partial complementary mediation: IAVR's impact on HCVC operates directly and indirectly by encouraging continuous learning in the healthcare sector. The indirect effect that is both significant and extensive highlights the role of CL as the connecting link between IAVR and the increase in HCVC. This implication leads to the conclusion that healthcare improvement interventions should not rely solely on IAVR promotion but also on fostering a culture of continuous learning.
Based on the study findings, the final structural equation model is presented in Figure 2:

Figure 2: Final structural equation model (n = 320)



Source: Field Data (2024)

Figure 2 presents the aggregated findings from the evaluation of both the measurement and structural models. The findings indicate that indicator loadings exceed 0.7, with path coefficients ranging from 0.173 to 0.542. The R^2 values indicate an explanatory power of 0.294 for the mediating construct (CL) and 0.390 for the endogenous construct (HCVC). The assessment results for both models are within acceptable parameters, suggesting that the final structural model is valid and reliable (Hair et al., 2010).

Discussion

From an OR perspective, the statistically significant but small direct effect of IAVR on HCVC (β = .173, t = 2.512, p = .012; f^2 = .035) suggests that innovation adoption value recognition contributes to healthcare value creation, although its direct practical effect is limited. The current literature emphasises the importance of embedding innovation within OR processes and organisational learning systems. Barriers such as organisational culture and poor data quality can hinder the effective introduction of technological innovation and subsequent value creation in healthcare (Brailsford et al., 2023; Tortorella et al., 2020).

On the other hand, the strong positive relationship between IAVR and CL (β = .542, t = 8.493, p < .001; f^2 = .417) demonstrates the importance of fostering organizational learning because this concept lies in the basis of the methodologies like Lean and Six Sigma and contributes to the ongoing improvement of the processes. It means that the implementation of IAVR in the public healthcare system may help develop a learning culture and increase organizational flexibility and decision-making quality.

Findings of the study indicate that CL exerts a medium, statistically significant influence on HCVC (β = 0.514, t = 6.958, p < 0.001; f^2 = 0.306), underscoring that CL is a crucial driver of value creation in public healthcare system operations. In OR, learning loops influence continuous process refinement, error correction, and performance improvement, all of which are essential to delivering high-quality, patient-centred services. Recent studies in healthcare using OR techniques substantiate this conclusion. A good example is the use of reinforcement learning, which demonstrates how adaptive decision-making frameworks help create and deliver better healthcare services (Wu et al., 2025). Moreover, OR studies indicate that successful implementation is closely related to the organisation's learning and culture (Brailsford et al., 2023). The moderate effect size observed in this study may reflect contextual limitations such as poor infrastructure or resource scarcity, which means that although CL is an important factor, its impact may still be constrained by organisational bottlenecks.

The findings indicate that IAVR significantly influences CL and that CL, in turn, contributes to HCVC, with CL serving as a key mediator between IAVR and HCVC. Although the model exhibits weak-to-moderate explanatory power (R^2 = 29.4% for CL and 39.0% for HCVC), the positive Q^2predict values (0.090–0.225) indicate predictive relevance, while the magnitude of predictive performance remains limited. The large IAVR-to-CL effect (f^2 = 0.417) and medium CL-to-HCVC effect (f^2 = 0.306) highlight the importance of strengthening both IAVR and CL to improve HCVC.

The mediation analysis confirms that CL mediates the relationship between IAVR and HCVC (indirect β = 0.279, SE = 0.047, 95% CI [0.187, 0.371], p < 0.001), whereas the direct effect remains statistically significant but reduced. This indicates complementary partial mediation: IAVR enhances HCVC both directly and through CL's mediating effects. From an OR lens, this is a critical insight because system-wide value creation is maximised when innovation adoption and continuous learning are co-instituted within operational processes. OR models of healthcare improvement emphasise that the adoption of innovation embedded in continuous learning systems leads to sustained performance improvement (Tortorella et al., 2020). Furthermore, the OR dialogues on the implementation of healthcare processes emphasise that, in the absence of an internal advocate and learning systems, innovations often fail to achieve the desired performance outcomes (Brailsford et al., 2023). Therefore, the current research reiterates that the synergy between IAVR and CL is a prerequisite for delivering significant healthcare value.

Conclusions

This study examined the influence of IAVR on HCVC in Tanzania's public healthcare system, with a particular focus on the mediating effect of CL. The results robustly supported all four hypotheses: IAVR exerts a statistically significant influence on HCVC, though it offers only a modest direct influence; it substantially fosters CL; and CL itself significantly enhances HCVC. Crucially, CL mediates the influence of IAVR, amplifying its influence on HCVC. From an OR perspective, these results emphasise that while introducing IAVR practices is necessary, their true potential is realised only when embedded within a culture of CL. The research highlights that operations and healthcare customer value optimisation are achievable not solely because of IAVR, but also because of its systematic integration with an adaptive CL culture. This synergistic integration fosters the potential for Tanzania's public healthcare system to demonstrate the most outstanding active responsiveness and improved alignment with healthcare customer needs, the hallmarks of effective public healthcare system operations management.

Implications

The findings of this research highlight valuable insights for OR in Tanzania's public healthcare system, from policy, practical, and theoretical perspectives. From a policy standpoint, the results highlight the necessity of embedding CL within national and facility-level innovation strategies to sustain improvements in healthcare delivery. In practice, it is advised that healthcare managers and practitioners

make regular professional development a part of their operations and also integrate CL into their daily routines to be able to take full advantage of the new technologies and, at the same time, optimise the acquisition, allocation and patient flow of the resources, even in settings where resources are limited. Theoretically, this research demonstrates that CL is a critical mediator of the causal relationship between IAVR and HCVC in the public healthcare system. As such, future OR models should formalise the relationship between CL and IAVR, and the uptake of these during HCVC processes, to better inform evidence-based decision-making for optimised resource acquisition and allocation in public healthcare systems.

Limitations of the research

The main limitation of the research is that it used only quantitative, cross-sectional methods, which are very helpful for identifying patterns but may also simplify public healthcare systems' operations. In addition, self-administered structured questionnaires can limit responses to some extent, leading to respondent bias; thus, the authors may have missed contextual factors and nuances already present in the culture or behaviour of the healthcare organisation or system. Furthermore, the study's design precludes drawing causal inferences or observing how processes and outcomes evolve.

Future researchers are advised to adopt a broader operational research perspective using mixed methods and longitudinal designs. Qualitative approaches and long-term studies would offer more profound insight into the dynamics of IAVR and CL, while capturing the evolving nature of operational improvements. Expanding research to include organisational and system-level factors and comparing across different public healthcare system settings would further enhance the practical relevance and applicability of findings, ultimately supporting more effective and sustainable public healthcare interventions.

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