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RESEARCH ARTICLE

Determinants of ICT Adoption and Performance in Healthcare: The Role of Individual Attributes and Organizational Contextual Factors

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ABSTRACT Implementing Information and Communication Technologies (ICTs) in the healthcare sector faces several barriers, and the pace of adoption may vary depending on several factors, including individual attributes such as competence and experience, along with contextual factors such as size, type, and location of the organization. We conducted a global survey involving healthcare professionals (n = 204) to understand the role of various determinants in adopting ICTs and their implications for organizational performance. Data was analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) and multiple regression for micro-level constructs. Findings indicate that while individual attributes positively influence organizational performance, the direct impact of ICT adoption on performance is limited. While front-end technologies enhance performance, base technologies may occasionally hinder it. This stresses the necessity of thoroughly assessing specific technology applications to ensure they operate effectively. Furthermore, the relationships between competence and experience in ICT adoption were not statistically significant, indicating that individual attributes may have less influence on ICT adoption; this implies that technological advancements typically occur through management decisions in collaboration with the relevant IT department, emphasizing the importance of increased user participation and the process of adoption and effective use, which are distinct aspects while evaluating individual aspects. Future research should focus on detailed and specific applications of technology and nuanced, long-term performance outcomes.

INDEX TERMS ICT adoption, organizational factors, digital transformation, healthcare 4.0, digital health, technology assessment.

I. INTRODUCTION

The melioration of healthcare systems is pivotal in elevating global life expectancy and navigating the healthcare sector through its status as one of the most formidable industries.

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Integrating Information and Communication Technologies (ICTs) is an indispensable strategy for transcending the confines of traditional hospital-centric care. The adoption of ICTs opens pathways toward a paradigm shift, ushering in a new era of virtual and distributed healthcare that harnesses the power of cutting-edge technologies [37], [90]. The usage of these technologies helps the healthcare service delivery in comprehensiveness, accessibility, coverage, continuity, quality, person-centeredness, coordination, accountability, and efficiency [79]. By way of example, clinical applications of ICTs encompass remote diagnosis, surgical procedures, image transmission, video consultations, and ongoing data analysis. Electronic Medical Records (EMRs) play a crucial role in minimizing the repetition of diagnostic tests and ensuring that patient information remains up to date. For patients with chronic diseases, ICT dramatically improves long-term health outcomes and reduces costs through continuous monitoring and timely adjustments to treatment [15]. Organizations across sectors face growing pressure to embrace Industry 4.0 technologies to improve performance [46], [89]. Healthcare is the slowest of all industries to adopt digital technologies [13], as it primarily engages a patient-specific 'human–human' interaction for its services compared to other industries [57]. Several barriers can affect the effectiveness of ICTs. For instance, a hospital may need to ensure enough infrastructure is available and the staff has sufficient knowledge, competency, and experience to utilize technologies adequately [39], [48], [82].

Competence and experience influence workers' readiness to embrace technology-induced change. They are closely related to each other. Competence refers to a worker's skills, knowledge, and abilities in a particular area. Competent employees are better equipped for evolving job demands and workplace changes, reflecting proficiency in technical, methodological, social, and personal competencies [39]. Technical competence involves adept utilization of ICTs, efficient data processing, and work virtually, encompassing relevant sub-skills. Methodological competence showcases innovation, strategic engagement, effective problem-solving, and learning continuously with associated sub-skills. Social competence refers to individuals' ability to work with people from diverse backgrounds, utilize knowledge networks, transfer work and knowledge, and take on more responsibilities. Personal competence signifies one's ability to be flexible with job profiles, accept changes, be ready to learn new things and support sustainable initiatives, manage pressure, and understand regulatory requirements [48]. Various other determinants influence an organization's innovation capability, including environmental conditions, structural frameworks, cultural paradigms, and organizational size, and the financial implications of innovation, such as the investment required, the potential economic gains, and the risks of failure. Notably, organizational size is particularly significant, with larger entities often exerting a dominant influence in their industries [85]. Organizations with over 500 employees are classified as large, while those with fewer are deemed small [1]. A strong correlation exists between hospital size and the adoption of new technologies, with research indicating a generally positive relationship between organizational size and technology adoption [21]. One perspective asserts that larger organizations possess the necessary resources to acquire innovations, while another suggests that their size provides a sufficient scale that facilitates the adoption of specific innovations [52]. Additionally, larger organizations typically have a diverse array of assets—financial, human, and expertise—that can be allocated to innovation [3]. In contrast, small organizations often struggle to remain competitive due to reluctance or inability to invest in improvement initiatives and new technologies [51]. Countries allocate a substantial portion of their economies to healthcare infrastructure. Despite significant investments in developing nations, a gap persists between available resources and increasing health needs [63]. While developed countries strive to provide universal access to healthcare services, ensuring affordable preventive, curative, and rehabilitative care, this remains difficult to achieve for developing regions [60]. The classification of countries into income groups—high, middle, and low—reveals considerable disparities in healthcare spending and infrastructure [91], positioning hospitals in high-income countries as early adopters of new technologies. Furthermore, private hospitals tend to exhibit more substantial expenditures on infrastructure and innovation compared to their public counterparts [81]. An innovative mindset is essential for adopting Industry 4.0 applications [39], yet public sector innovativeness is often hindered by weak leadership, bureaucratic structures, and a lack of competition [36], [72]. Consequently, patients frequently resort to private healthcare services due to inadequate infrastructure and personnel in public facilities [8].

This research examines various individual attributes and organizational contextual factors that affect the adoption of ICTs and their performance implications in the healthcare sector. We will first assess the extent to which hospitals have integrated ICTs for digitalization. Next, we will analyze how healthcare workers' competence and experience, along with contextual factors such as hospital size, type, and location, affect ICT adoption levels and how experience contributes to competence development. Subsequently, we will measure organizational performance indicators, defined as achieving explicit goals that reflect stakeholder values. Existing literature indicates a positive correlation between ICT adoption and organizational performance [41], [84]. Key performance indicators for hospitals include cost-effectiveness [31], [67], [71], [84], productivity [31], [35], [50], [84], quality of treatment [31], [35], [84], patient satisfaction [4], [31], [35], [84], patient safety [4], [35], [84], [94], staff safety [68], [70], [84] and job satisfaction [62], [76], [96]. Finally, we will evaluate the impact of ICT adoption and individual attributes, such as competence and experience, on overall organizational performance.

TABLE 1. Comparative analysis of factors influencing ICT adoption in healthcare.

Title	Author(s)	Type of study	Factors discussed for ICT adoption
Managing ICT in Healthcare Organization: Culture, Challenges, and Issues of Technology Adoption and Implementation	Zakaria et al., 2010[95]	Case study	Supportive organizational culture, competent IT workers, committed IT department and heavy investment on ICT infrastructure are key factors
Organizational Influences on Health Care System Adoption and Use of Advanced Health Information Technology Capabilities	Norton et al., 2019[64]	Survey	Organizational Structure, Resource Allocation Practices, Standardization Practices
The Assessment of Big Data Adoption Readiness with a Technology–Organization–Environment Framework: A Perspective towards Healthcare Employees	Ghaleb et al., 2021[28]	Survey	Technology–organization–environment (TOE) factors for Bigdata adoption
This study		Survey	Considers individual attributes such as competence and experience, and organizational contextual factors such as location, type and size on adopting ICTs in healthcare.

The implementation of ICTs has previously been studied using various frameworks with specific objectives, to cite a few (i) Device selection Matrix to decide the right ICT device based on technical, organizational, and economical parameters [12], (ii) to monitor development stages of ICTs [23], (iii) Technology, Economic, Market, Political, Evaluation, Social, and Transformation (TEMPEST) model for understanding benefits and barriers in ICT adoption [19], (iv) Health Services Research framework that assesses access, quality, and costs of care [32], and (v) to assess business models to innovate health care [33]. The pertinence of our research is accentuated by its capacity to inform policy formulation and strategic initiatives in healthcare management, particularly in advancing digital transformation endeavors. It addresses a pivotal lacuna in scholarly discourse by correlating ICT adoption with various individual determinants and organizational contextual factors, offering profound insights for public and private healthcare entities striving to augment care delivery and operational efficacy. Table 1 represents how our study stands out compared to existing research discussing factors on ICT adoption in healthcare.

Nine relationships were examined in this comparative evaluation (Figure 1), corresponding to three sets of research hypotheses: individual attributes with adopting ICTs, contextual factors affecting ICT adoption, and aspects impacting organizational performance.

H1.1: The level of professional competence with ICTs positively affects ICT adoption.

H1.2: The healthcare worker's experience with ICTs positively impacts ICT adoption.

H1.3: The healthcare worker's experience with ICTs positively impacts competence development.

H2.1: Healthcare organizations in higher-income countries adopt ICTs quicker than those in middle-income countries.

H2.2: Healthcare organizations in the private sector adopt ICTs faster than public ones.

H2.3: The size of the healthcare organization positively influences ICT adoption.

H3.1: The professional competence positively impacts organizational performance.

H3.2: The healthcare worker's experience with ICTs positively impacts organizational performance.

H3.3: The ICT adoption positively impacts the performance of healthcare organizations.

II. MATERIAL AND METHODS

A. DATA COLLECTION AND SAMPLE CHARACTERISTICS

We conducted a structured survey to collect quantitative data from healthcare professionals across seven countries - Argentina, Australia, Chile, India, Ireland, Peru, and the United Kingdom. The survey targeted medical and paramedical professionals who started using ICTs, which were administered from June 2022 through May 2023, in English and localized languages where necessary to enhance accessibility. A pre-test of the survey instruments was conducted with a sample size of 25 targeted respondents; based on their feedback, questions were updated, especially providing a brief explanation of each technology in the healthcare sector's context, nullifying the measurement errors. The pilot study data was excluded from the data analysis. The instrument was further scrutinized by four experts (two from industry and three from academia), ensuring its face and content validity, and minor suggestions were incorporated before administrating the survey to the intended population. To reduce the sampling error, we randomly selected target participants. The coverage error was avoided by offering a multi-mode of surveys, including online and paper versions, based on the participant's preference. Data was securely stored, access

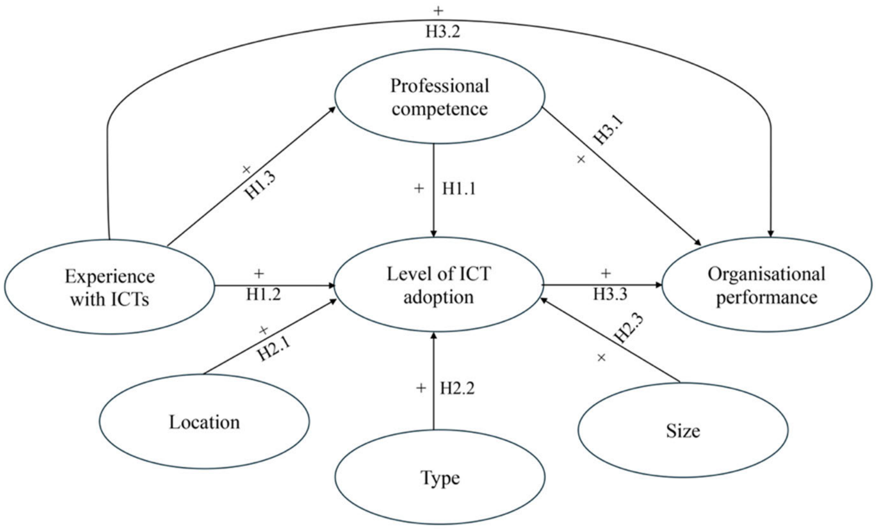

FIGURE 1. **Paths based on hypotheses formulation.**

restricted to the research team, and personal identities were kept confidential in this report. The study's purpose and data usage were explained to all participants through a cover letter. They were guaranteed that their responses would remain confidential and their identities would not be disclosed in research reports and publications. Finally, those who agreed to participate in the survey were asked to sign a consent form, and participants had the option to quit the survey at any time [58]. The study protocol and consent forms have been reviewed and approved by the Scientific Ethics Committee for Health Sciences of the Pontificia Universidad Católica de Chile (Protocol ID: 210331002). There were 241 completed responses. The flowchart illustrating the steps involved in data collection and analysis is shown in Figure 2.

The survey instrument's design facilitated the exit of participants who lacked experience with ICTs. Consequently, a final sample size of 204 was obtained for data analysis, surpassing the minimum required of 161, as determined by the priori sample size calculator for structural equation models developed by Daniel Soper [80]. An extended Likert scale is utilized to assess the nuanced dimensions of professional competence—technical, methodological, social, and personal—that are not directly measurable through conventional surveys. The detailed sample characteristics and a country-wise count of participants based on their role, type of hospital, and size of hospital are provided in Table 2. The survey questionnaire included in Appendix A (in supplementary materials) was designed as a self-assessment instrument.

The heat map of the level of ICT adoption and organizational performance indicators are provided in Figure 3 and Figure 4, respectively. Based on the responses, technologies such as the Internet of Things (IoT) and biomedical sensors are moderately adopted, with a mean of 3.43 (SD=1.08) and 2.93 (SD=1.30), respectively. On the other hand, technologies such as 3D printing and collaborative robotics have the lowest adoption rate, with mean scores of 1.26 (SD = 0.70) and 1.39 (SD = 0.91), respectively. Also, the organizational performance indicators, such as quality of treatment with a

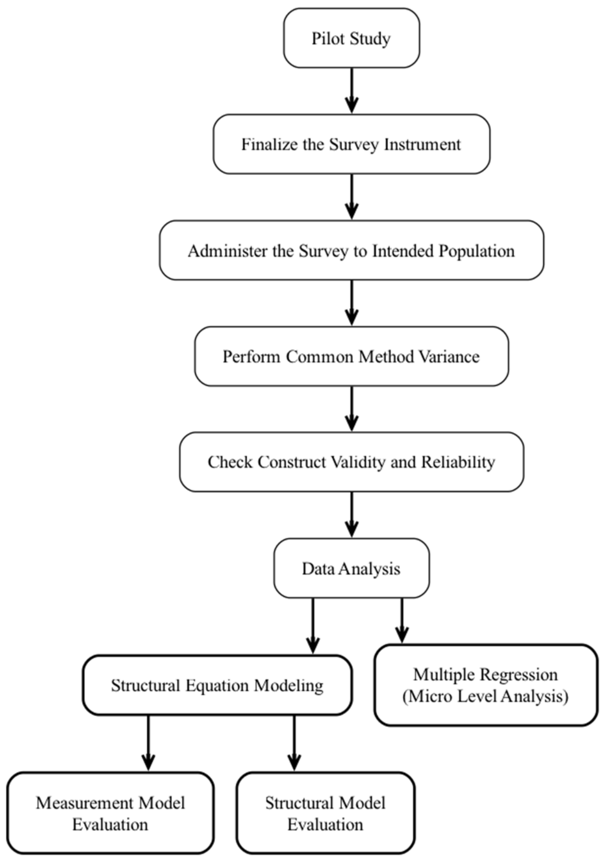

FIGURE 2. **Flowchart illustrating the steps involved in data collection and data analysis.**

TABLE 2. Sample characteristics (n = 204).

Description	Frequency	Percentage (%)	
Country where the hospital is located?			
Australia	15	7.4	High-Income countries: 55.4
Chile	58	28.4	
Ireland	21	10.3	
United Kingdom	19	9.3	
Argentina	25	12.3	Middle-income countries: 44.6
India	48	23.5	
Peru	18	8.8	
Type of hospital			
Public	78	38.2	
Private	126	61.8	
Hospital size in terms of number of employees			
Less than 50 employees	14	6.9	
Between 50 - 500 employees	74	36.3	
More than 500 employees	116	56.9	
Age of the participant			
Between 18-25	11	5.4	
Between 26-35	71	34.8	
Between 36-45	71	34.8	
Between 46-60	49	24.0	
More than 60	2	1.0	
Profession			
Doctor	74	36.3	
Nurse	97	47.5	
Others	33	16.1	
Experience in handling ICTs			
0 - 1 year	12	5.9	
1 -3 years	14	6.9	
3-8 years	32	25.5	
More than 8 years	126	61.8	

Country specific details (Participant's count in numbers)

Country	Role			Type		Size	
	Doctor	Nurse	Others	Public	Private	More than 500 employees	Less than500 employees
Argentina	8	12	5	7	18	23	2
Australia	5	10	0	11	4	8	7
Chile	35	18	5	8	50	48	10
India	12	25	11	15	33	4	44
Ireland	5	16	0	12	9	13	8
Peru	2	6	10	7	11	2	16
United Kingdom	7	10	2	18	1	18	1

mean of 4.11 (SD = 0.89) and patient safety with a mean of 4.0 (SD = 0.91), have shown the most improvement recently (in the last 2-3 years), followed by patient satisfaction with a mean of 3.83 (SD = 0.95), and productivity with a mean of 3.82 (SD = 1.00). All the performance metrics have improved, with cost-effectiveness being the lowest, with a mean of 3.41 (SD = 1.14). Finally, 177 out of 204 (86.8%) participants reported increased digital technology usage due to COVID-19.

B. ASSESSMENT OF COMMON METHOD VARIANCE

Given that our study relies on self-reported measures of the level of ICT adoption, competence, and performance indicators, we took measures to address and evaluate the potential influence of common method variance (CMV), as advised by previous scholarly work [69]. To mitigate this concern procedurally, we ensured stringent confidentiality and anonymity measures for participants, fending against contrived or insincere responses. We employed statistical methodologies for

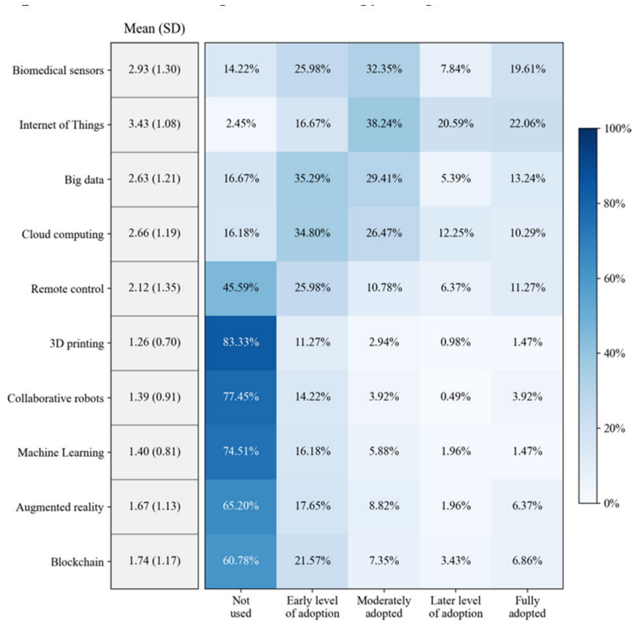

FIGURE 3. Heat map of the level of ICT adoption.

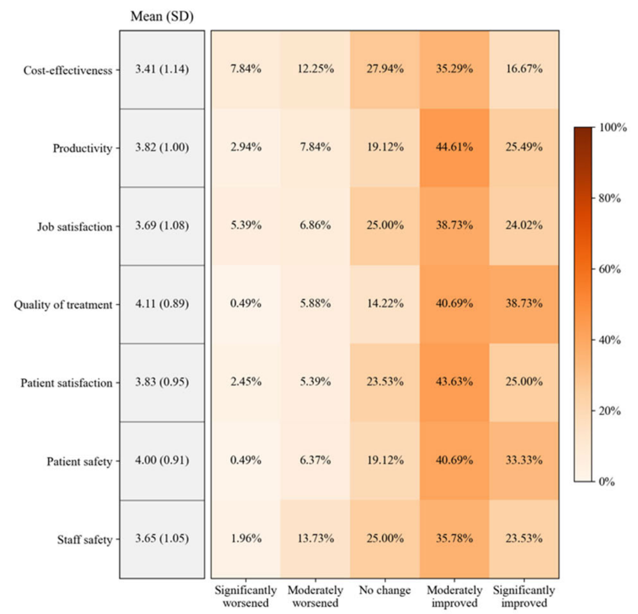

FIGURE 4. Heat map of organizational performance.

further assurance in tandem with these procedural actions. Firstly, we conducted Harman's single-factor test, revealing that a solitary factor accounted for only 20.1% of the total variance, notably below the 50% threshold, indicating a lack of substantive CMV in our investigation. Secondly, we conducted an exhaustive collinearity assessment, aligning with the endorsed PLS-SEM data analysis approach [53]. This examination involved scrutinizing variance inflation factors (VIF), where values surpassing 3.3 indicate collinearity and CMV. Our meticulous analysis unveiled VIF values spanning from 1.38 to 2.29, further substantiating the absence of significant CMV influence within our research scope.

C. CONSTRUCT VALIDITY AND RELIABILITY

We performed an exploratory factor analysis (EFA) using principal component extraction to validate constructs using questionnaire responses for the level of ICT adoption to identify the latent constructs underlying measured variables [24]. We haven't had any priory hypotheses on how the underlying factors would turn out, which matches the recommendations of Finch and West [25]. Before performing the factor analysis, Kaiser-Meyer-Olkin (KMO), a measure of sampling adequacy (> 0.50 referred to as acceptable), and Bartlett's Test of Sphericity (BTS) ($p < .05$ referred to as suitable), are carried out [92]. Considering the potential correlations across the indicators, we used "Oblimin" rotation for both the EFAs [18]. For the EFA of the level of ICT adoption, KMO is reported as 0.89, and BTS is 1,072.67 ($df = 45$, $p < 0.001$), and both were found within acceptable limits. We retained two factors with eigenvalues larger than 1. The factor loadings indicate that technologies such as biomedical sensors, the IoT, Big data, cloud computing, and remote control are strongly associated with factor 1 and 3D printing, collaborative robotics, machine learning, augmented reality, and blockchain are associated with factor 2. Aligning with Frank et al. [27], based on the implementation pattern of Industry 4.0 technologies, we named the first factor as base technologies and the second factor as front-end technologies. The KMO for the performance indicators was reported as 0.849, and the BTS was 613.81 ($df = 21$, $p < .001$), and both were found within the acceptable limits. After evaluating the eigenvalues, only one factor was extracted. The results of PCA for the level of ICT adoption and hospital performance indicators are given in Table 3.

D. PARTIAL LEAST SQUARED STRUCTURAL EQUATION MODELLING

The study used partial least squares-structural equation modelling (PLS-SEM), a variance-based technique to analyze the data, suitable when the research contains higher-order constructs and complex model structures and tests the hypothesized research model [49] and the analysis carried out in R programming utilizing the package named SEMinR [74]. Compared to covariance-based Square-Structural Equation Modelling, it works better in small sample-size studies. It is a multistage analysis consisting of measurement and structural model evaluation [93].

1) MEASUREMENT MODEL EVALUATION

The model evaluation begins with examining the indicator reliability. The items are eliminated when the outer loading is below 0.40. Then, the construct's internal consistency reliability and convergent validity thresholds were assessed. Indicators were removed (refer to Table 4) when construct measures did not meet the recommended thresholds [34]

TABLE 3. PCA results of the level of ICT adoption and hospital performance indicators.

Variables	Mean	SD	Communalities	Factor loading		Factor name
Level of ICT adoption						
Biomedical sensor	2.93	1.301	0.64	0.79	0.01	Base technologies
Internet of things	3.43	1.082	0.73	0.93	-0.20	
Bigdata	2.63	1.214	0.71	0.79	0.11	
Cloud computing	2.65	1.191	0.73	0.75	0.19	
Remote controlling	2.11	1.352	0.66	0.68	0.23	
3D Printing	1.25	0.699	0.60	-0.15	0.83	Front-end technologies
Collaborative robotics	1.39	0.905	0.73	0.02	0.85	
Machine learning	1.40	0.808	0.61	0.03	0.76	
Augmented reality	1.67	1.134	0.63	0.10	0.74	
Blockchain	1.74	1.172	0.65	0.24	0.67	
Performance indicators						
Cost-effectiveness	3.41	1.139	0.40	0.63		Organizational performance
Productivity	3.83	0.998	0.61	0.78		
Job satisfaction	3.69	1.077	0.59	0.77		
Quality of treatment	4.11	0.894	0.59	0.77		
Patient satisfaction	3.83	0.948	0.63	0.79		
Patient safety	4.00	0.910	0.56	0.75		
Staff safety	3.64	1.046	0.50	0.71		

and they were re-evaluated. The primary measure of internal consistency is Jöreskog's [47] composite reliability rhoc. Higher values indicate higher reliability and values over 0.70 are considered acceptable. Additionally, Cronbach's alpha is measured for indicator reliability, with a threshold of 0.70 [65]. Convergent validity is used to check whether the indicators represent the underlying factors, and the average variance extracted (AVE) is used to evaluate convergent validity. AVE > 0.50 indicates that, on average, the construct explains more than half of the variance of its indicators [26]. To assess the discriminant validity, the Fornell–Larcker (FL) Criterion [26], i.e. the square root of the AVE of each factor, should be greater than the correlation coefficients between the factor in question and other factors. Also, Heterotrait-Monotrait (HTMT) ratio, i.e., HTMT value above 0.90, suggests a lack of discriminant validity [40] were evaluated and found parameters within the limit. Table 4 provides the Item loadings, reliability, convergent validity, and VIF of indicators of the model.

Table 5 provides the discriminant validity results. Diagonal elements are the square roots of the average variance extracted (AVE). Below the diagonal elements are the correlations between the constructs' values. Above the diagonal elements are the HTMT values. The convergent validity and discriminant validity of the higher-order constructs were carried out as per the recommendations of Vigoda-Gadot et al. [86], i.e., The higher-order components are evaluated for their discriminant validity among themselves and in relation to all other components in the model except with its own indicators used to identify the higher-order component and found within the criteria.

2) STRUCTURAL MODEL EVALUATION

The structural model consists of a higher composite named level of ICT adoption formed by joining base technologies and front-end technologies; a higher composite called professional competence is formed by combining technical, methodological, social and personal competencies and binary item constructs such as type of the organization, size of the hospital (in number of employees), and location of the hospital (located in higher income countries), composites called experience with digital technologies and organizational performance. Assessment of the structural model begins with checking potential collinearity, which may bias the path coefficient. The VIF (< 5) is the measure of the potential collinearity [34]. Our model has a VIF of 1.104, suggesting no collinearity problem in the structural model. Next, the path coefficients and their significance were assessed. We tested hypotheses with a bootstrapping technique using 10,000 bootstrap samples, no sign changes option, and 95% bias-corrected confidence intervals [42]. We have also performed a set of mediation effect analyses. First, we have checked for the indirect effect of experience in handling ICTs through competence to organizational performance and found a *Complementary mediation*, i.e., the indirect effect and the direct effect are significant and point in the same direction (the product of all three paths are positive, 0.021). Second, the indirect effect of experience handling digital technologies through the level of adoption of H4.0 technologies on organizational performance was found to be a *Direct-only non-mediation* as the direct effect is significant but not the indirect effect. Third, the indirect effect of experience in handling digital technologies through competence to the level of ICT adoption found a *no-effect non-mediation* as neither the direct nor the indirect effect is significant. Finally, for the indirect effect of competence in handling digital technologies, adopting ICTs to organizational performance also found a *direct-only non-mediation*. The path coefficients provided for direct relationships and mediation effects are listed in Table 6.

TABLE 4. Item loadings, reliability, convergent validity, and VIF.

Constructs	Λ	α	CR	AVE	VIF
Professional competence in handling ICTs					
Technical competence	-	0.826	0.878	0.593	-
State-of-the-art knowledge	0.690				1.508
Technical skills	0.863				2.269
Process understanding	0.835				2.224
Skill to assess need of technology	0.725				1.674
Data/information processing skills	Removed				-
Handling smart devices, apps, smart media	0.720				1.476
Understanding IT security	Removed				-
Methodological competence	-	0.819	0.866	0.523	-
Creativity	0.533				1.385
Entrepreneurial thinking	0.753				1.647
Problem solving	0.691				1.679
Conflict solving	0.773				1.867
Decision making	0.773				1.870
Analytical skills	0.783				1.798
Research skills	Removed				-
Efficiency orientation	Removed				-
Social competence	-	0.865	0.893	0.548	-
Intercultural skills	Removed				-
Language skills	Removed				-
Communication skills	0.721				1.625
Networking skills	0.495				1.315
Ability to work in a team	0.767				2.291
Collaboration skills	0.799				2.019
Ability to be compromising and cooperative	0.779				2.198
Ability to transfer knowledge	0.817				2.371
Leadership skills	0.752				1.590
Personal competence	-	0.829	0.860	0.510	-
Flexibility	0.730				1.666
Ambiguity tolerance	0.830				1.802
Motivation to learn	0.750				2.159
Ability to work under pressure	0.527				1.509
Sustainable mindset	0.623				1.383
Compliance	0.782				1.511
Level of ICT adoption					
Base technologies	-	0.881	0.913	0.677	-
Biomedical sensors	0.808				2.057
Internet of Things	0.807				1.992
Bigdata	0.827				2.517
Cloud computing	0.855				2.591
Remote monitoring	0.817				2.163
Front-end technologies	-	0.854	0.886	0.633	-
3D printing	0.729				1.581
Collaborative Robotics	0.859				2.255
Machine learning	0.785				1.778
Augmented reality	0.784				1.937
Blockchain	0.815				2.040
Performance Indicators					
Organizational performance	-	0.865	0.896	0.552	-
Cost-effectiveness	0.663				1.547
Productivity	0.821				2.135
Job satisfaction	0.771				1.931
Quality of treatment	0.772				1.909
Patient satisfaction	0.789				2.029
Patient safety	0.706				2.271
Staff safety	0.663				1.962

TABLE 5. Discriminant validity results.

-	Technical Competence	Methodological Competence	Social Competence	Personal Competence	Base technologies	Front-end technologies	Organizational Performance
Technical Competence	0.770	0.605	0.307	0.330	0.156	0.154	0.455
Methodological Competence	0.511	0.723	0.467	0.584	0.230	0.135	0.501
Social Competence	0.247	0.363	0.740	0.887	0.098	0.089	0.199
Personal Competence	0.330	0.487	0.719	0.714	0.101	0.127	0.172
Base technologies	−0.124	−0.222	−0.016	0.006	0.823	0.632	0.169
Front-end technologies	0.086	0.067	0.014	0.106	0.551	0.795	0.135
Organizational performance	0.402	0.450	0.177	0.153	−0.131	*0.083*	0.743

TABLE 6. Results of structural model evaluation.

Relationship	Path coefficient	T Stat.	2.5% CI	97.5% CI	Decision
Professional competence → Level of ICT adoption	0.032	0.357	-0.156	0.189	H1.1 Rejected
Experience in handling ICTs → Level of ICT adoption	-0.028	-0.428	-0.154	0.100	H1.2 Rejected
Total Digital Exp. > 3 years → Professional competence	0.238***	3.421	0.123	0.393	H1.3 Supported
High Income Country → Level of ICT adoption	0.362***	5.374	0.228	0.491	H2.1 Supported
Being Private → Level of ICT adoption	0.265***	5.095	0.163	0.367	H2.2 Supported
More than 500 employees → Level of ICT adoption	0.271***	4.082	0.139	0.400	H2.3 Supported
Professional competence → Organizational performance	0.406***	5.537	0.290	0.566	H3.1 Supported
Total Digital Exp.> 3 years → Organizational performance	0.222***	3.275	0.073	0.339	H3.2 Supported
Level of ICT adoption → Organizational performance	-0.019	-0.295	-0.140	0.112	H3.3 Rejected
Mediation effects	**Path coefficient**	**T Stat.**	**2.5% CI**	**97.5% CI**	**Type of Mediation**
Total Digital Exp. > 3 years → Professional competence → Organizational performance	0.096**	2.600	0.047	0.191	Complementary mediation
Total Digital Exp. > 3 years → Level of ICT adoption → Organizational performance	0.001	0.114	-0.011	0.009	Direct only non-mediation
Total Digital Exp. > 3 years → Professional competence → Level of ICT adoption	0.007	0.313	-0.044	0.053	No-effect non-mediation
Professional competence → Level of ICT adoption → Organizational performance	-0.001	-0.099	-0.012	0.014	Direct-only non-mediation

Note: *** significant at 1%, ** significant at 5%

In the next step, we evaluated the coefficient of determination (R^2 value) for predictive power. Cohen [16] suggested R^2 values for endogenous latent variables are assessed as follows: $R^2 = 0.26$ as large effect size, $R^2 = 0.13$ as medium effect size, and $R^2 = 0.02$ as small effect size. The proposed model accounted for 26% of the variance ($R^2 = 0.26$) in organisational performance, which is a large effect size, 31% of the variance ($R^2 = 0.31$) in the level of ICT adoption, which is also a large effect size, and 6% of the variance ($R^2 = 0.06$) in level of competence, which is laying in small to medium effect size range. Additionally, the effect size is also represented with the f^2 value, which is a coefficient that represents how a variable in a structural model may be influenced by several different variables. Effects with f^2 values ≥ 0.35, ≥ 0.15, and ≥ 0.02 are interpreted as strong, moderate, and weak, respectively [16]. Out of all the significant paths, for the professional competence → Organizational performance, $f^2 = 0.19$, for the total exp. >3 years

→ professional competence; $f^2 = 0.06$, for the total exp. >3 years → organizational performance; $f^2 = 0.07$, for the total exp. >3 years → the level of ICT adoption; $f^2 = 0.001$, for high income country → the level of adoption of H4.0 technologies; $f^2 = 0.14$, for being private → the level of ICT; $f^2 = 0.10$, and for more than 500 employees → the level of ICT adoption; $f2 = 0.08$. As a final course of action in the data analysis model's predictive power was evaluated. The prediction error of the endogenous constructs was evaluated, and most of them were non-symmetric, as evidenced by a long left or right tail in the distribution of prediction errors [22]. Shmueli et al. [77] suggest that mean absolute error (MAE) is the more appropriate prediction statistic to look for on such occasions. While comparing each indicator's PLS out-of-sample metrics MAE values with a naïve linear regression model (LM) benchmark, more than half of the indicators in the PLS-SEM analysis yield smaller prediction errors than the LM, indicating a medium predictive power [34].

E. MICRO-LEVEL ANALYSIS OF CONSTRUCTS WITH MULTIPLE REGRESSION

The present study employs PLS-SEM as its analytical framework, albeit acknowledging its limitations in effectively integrating construct analyses down to the micro level in a single model. In addressing this modelling limitation, i.e., paths from the same constructs and the higher composite with the same construct to endogenous variables in a single model will persuade perfect collinearity, micro-level analysis of constructs under two of the higher composites, namely the level of ICT adoption and competence in handling digital technologies are considered to predict the performance of the organization. Gilbert and Shult [29] suggest considering the multi-level analysis model for variables with subgroups. This approach helps to achieve a granular assessment of constructs, such as delineating the impacts of the adoption levels of both base and front-end technologies on organizational performance and individual competence types on organizational performance. In pursuit of a micro-level evaluation, we augment the PLS-SEM methodology with multiple regression analyses. These regressions center around pertinent factors identified in our previous analysis using PLS-SEM. Given the satisfactory construct validity and reliability levels established in prior phases, we judiciously forego redundant replication of these preliminary steps.

The initial regression analysis involves leveraging the factor scores derived from the EFA applied to base and front-end technologies. These factor scores are enlisted as predictors in assessing their influence on organizational performance outcomes (Model 1). Concurrently, we conduct confirmatory factor analysis on the retained competence variables, as per Table 3. Subsequently, the factor scores corresponding to distinct competency types—technical, methodological, social, and personal—are subjected to regression against organizational performance indicators (Model 2) to discern the varying degrees of influence individual competencies exert on overall organizational performance.

TABLE 7. Standardized $\hat{\beta}$ coefficients for the regression analyses.

Variables	Organizational performance	
	Model 1	Model 2
Base Technologies	-0.203***	
Front-end Technologies	0.174**	
Technical Competence		0.327**
Methodological Competence		0.530***
Social Competence		-0.125
Personal competence		0.086
F-Value	4.203**	10.25***
R^2	0.04	0.17

Note: ** significant at 5%; *** significant at 1%

III. RESULTS

A. FINDINGS BASED ON PLS-SEM

The results reveal the lack of statistical significance in the path coefficient analysis suggests insufficient evidence to confirm the anticipated positive impact of professional competence on the level of ICT adoption ($\beta = 0.032$, t = 0.357, 95% CI = −0.156, 0.189). Hence, H1.1 was rejected. The path coefficient analysis does not reveal a statistically significant relationship between the experience of digital technologies and the level of ICT adoption ($\beta = -0.028$, t = −0.428,87 95% CI = −0.154, 0.100). This suggests that our initial hypothesis linking the variables may not hold in the observed context. Hence, H1.2 was not supported. The results also acknowledge the significant direct and positive effect of the experience of more than three years handling digital technologies against less than three years on competence development ($\beta = 0.238$, t = 3.421, 95% CI = 0.123, 0.393). Therefore, H1.3 was accepted. The observed path coefficient of the path from high-income countries against middle-income countries to level of ICT adoption provides robust empirical support for the positive influence hypothesized in our research model ($\beta = 0.362$, t = 5.374, 95% CI = 0.228, 0.491). These findings corroborate the theoretical underpinnings of our study. So, H2.1 was accepted. The model demonstrates a noteworthy positive association between a hospital being in the private sector compared to the public and the level of ICT adoption, as confirmed by the path coefficient analysis ($\beta = 0.265$, t = 5.095, 95% CI = 0.163, 0.367). This result provides substantial evidence supporting our initial hypothesis, H2.2. There exists a significant positive correlation between hospital size, measured by the number of employees (comparing those with more than 500 employees to those with fewer than 500), and the level of ICT adoption, as confirmed by the path coefficient analysis ($\beta = 0.271$, t = 4.082, 95% CI = 0.139, 0.400). These findings provide strong evidence in support of our initial hypothesis, H2.3.

The results indicate a strong positive effect of professional competence on organizational performance ($\beta = 0.406$, t = 5.537, 95% CI = 0.290, 0.566). Therefore, H3.1 was supported. Moreover, the empirical validation of the proposed link between experience in managing digital technologies and organizational performance revealed a statistically significant positive influence ($\beta = 0.222$, t = 3.275, 95% CI = 0.073, 0.339) further solidifies the theoretical foundation of our study; thus, H3.2 was supported. Finally, the lack of statistical significance in the path coefficient analysis suggests insufficient evidence to confirm the anticipated impact of ICT adoption on organizational performance ($\beta = -0.019$, t = -0.295, 95% CI = -0.140, 0.112). Hence, H3.3 was not supported. However, a micro-level assessment of the influence of base technologies and front-end technologies is performed using multiple regression analysis with their factor scores, and the results are discussed in the next session.

B. INSIGHTS DERIVED FROM MULTIPLE REGRESSION ANALYSIS

The results of the multiple regression suggest that model 1 is overall significant ($\boldsymbol{p}$ =.016) and the adoption of base technologies had a negative influence on organizational performance ($\hat{\beta} = -0.203$, $\boldsymbol{p}$ =.009), whereas the adoption of front-end technologies shows a positive influence on performance ($\hat{\beta} = 0.174$, $\boldsymbol{p}$ =.025). Model 2, which is overall significant ($\boldsymbol{p}$ <.001), showed a significant influence of technical ($\hat{\beta} = 0.327$, $\boldsymbol{p}$ =.037) and methodological competence ($\hat{\beta} = 0.530$, $\boldsymbol{p}$ =.002) on organizational performance and influence of social and personal competence on performance was not significant.

IV. DISCUSSIONS

A. INDIVIDUAL ATTRIBUTES ON ADOPTING ICTS AND ORGANIZATIONAL PERFORMANCE

The burgeoning significance of digital proficiency has emerged as a pivotal concern in workforce viability. This heightened importance is primarily attributable to the escalating demand for adept professionals capable of navigating a diverse array of ICT deployment across multifarious tasks, accentuating the imperative nature of digital competence in modern work [2], [39]. Professionals must possess new skills to steer the complexities of the workplace digital transformation. We have considered the combination of four types of competence recommended by Hecklau et al. [39] namely, technical, methodological, social, and personal competence, along with experience with ICTs. Healthcare professionals and organizations need to gain recognition of the imperative for forthcoming digital competencies. The onus lies in adequately equipping future healthcare professionals, necessitating training programs targeting digital competence [30], [75], and is vital to reducing digital alienation and digital divides in the sector [54]. Our research found a substantial impact of overall competence in handling ICTs on organizational performance. At an individual level, we found that the technical and methodological competencies majorly influence organizational performance. At the same time, social and personal competencies stand non-influential. Pacheco and Coello-Montecel [66] learned that digital competencies improve job performance while considering competencies pertinent to information navigation, creative aptitude, mobile utilization, and social acumen. The finding is consistent with previous research [17], [44] on how digital skills can enhance the workplace. The study found that professional competence did not have a significant impact on ICT adoption. This may be because other factors, such as lack of budget [7], [55], limited IT infrastructure [38], and resistance to change [5], could also be majorly influencing the adoption of digital technology. It is necessary to differentiate between the process of adoption and the effective utilization of digital technologies. This also points to a potential scenario where technology adoption led by managerial staff, rather than clinical staff, often faces increasing resistance to embrace and implement the technology [7], [10], [56]. Moreover, the adoption of ICT in the healthcare sector is still nascent, making it premature to draw definitive conclusions. Our findings align with existing studies showing technology competence's non-influential effect on adopting various technologies [83], [88].

On the other hand, the experience in handling ICTs is task-specific experience, which refers to the knowledge and expertise acquired through practical engagement with a particular task or domain. Through hands-on engagement with technology tailored to their specific tasks, employees enhance their proficiency and contribute to the overall organizational performance. Our study showed a significant relationship between having more experience (at least three years) handling digital health for organizational performance and competence development. Our findings align with the existing literature on task-specific experience's effect on individual outcomes [14], [45], [61] and organizational performance [11]. On the contrary, our finding suggests an insignificant relationship between experience handling digital health and adopting ICTs. The reason carries on being an extension to our expositions, similar to the impact of competence on the level of ICT adoption. i.e., the individual attributes stand non-influential for the technology adoption process, as the adoption largely depends on management's resolution and takes place with the involvement of IT professionals in a hospital.

B. INFLUENCE OF ICT ADOPTION ON ORGANIZATIONAL PERFORMANCE

The overall effect of ICT adoption on organizational performance was not significant. The previous studies exhibited a significant positive association between technology adoption and performance [41], [84]. However, the micro-level analysis of technology bundles, such as base and front-end, on organizational performance provided significant association. For instance, the impact of the adoption of base technologies on performance showed a negative relationship, while the adoption of front-end technologies displayed a positive relationship. In the case of base technologies, they are the set of technologies that hospitals consider during their initial digitalization phase [48]. The legacy systems which do not work efficiently due to a lack of interoperability and outdated configurations may cause a negative relationship between the adoption of base technologies and organizational performance. Bhattacherjee et al. [9] briefs another possibility that if a hospital upgraded the technology recently, it may not translate the adoption initiative to operational gains. The absence of proper planning for digitalization may also cause the unintended amplification of physicians' workloads and could affect their performance negatively. Conversely, adopting front-end technologies positively affects organizational performance, reflecting that the hospitals that adopted more advanced technologies showed superior performance and can be considered primarily serious adopters.

C. IMPACT OF CONTEXTUAL FACTORS ON ADOPTING ICTS

We found a positive relationship between hospitals in high-income countries and the level of ICT adoption compared to those in middle-income countries. It aligns with previous research on geographic location's impact as high-income countries facilitate innovation, research and development, infrastructure, and knowledge absorption [6]. Also, high-income countries have ambitious plans and are rushing to implement Industry 4.0 applications [73]. The function of private healthcare establishments is said to complement and support improvements to public healthcare, not supersede it [87]. Private health providers become key players where the public sector is inadequate and/or of low quality [78]. Our study proved that hospitals in the private sector significantly influence the adoption of ICTs. Our finding aligns with previous research [81] and supports this argument based on private institutions' quick procurement decisions compared to public ones, as several shortcomings in the form of red tape hinder the public sector in speeding up the process [59]. It can also be inferred that the delay may be due to the bureaucratic structure of the public organizations [36], [72]. Public institutions must address historical barriers that traditionally impede decision-making and innovative initiatives through effective organizational reforms [86]. Finally, the study manifests that larger hospitals (more than 500 employees) significantly influence the adoption of digital technologies. The finding is in line with the previous studies [20], [43].

D. IMPLICATIONS OF THE RESEARCH

Our study has yielded valuable insights that may benefit a wider audience. Firstly, this study contributes to the digital transformation literature regarding the various individual and organizational contextual aspects of adopting digital technologies, which is helpful in utilizing and developing tailored strategies for various healthcare environments. Secondly, it helps integrate the identified most prominent competence bundles as the critical element in building the internal capabilities to navigate the complex tasks for digitalisation and its successful utilization. Third, the study highlights the interplay between individual attributes (competence and experience) and their impact on organizational performance, along with the implementation of ICTs. Theoretical organizational behavior, organizational culture, leadership, change management, and technology adoption models can be refined to incorporate the nuanced associations between workforce attributes and technology implementation outcomes. Cultivating an organizational culture and leadership that actively fosters, supports, and implements creative and innovative solutions and technology changes is essential. Fourth, healthcare organizations can plan their resource allocation for professional competence development-related activities such as training sessions, knowledge sharing and learning platforms, and evaluations based on the assessment. Finally, this paper critically views a potential prevailing practice in which management generally makes technology adoption decisions with minimal involvement of end users. Stakeholders may need to reflect on this scenario and guarantee effective user engagement in digitalization.

E. LIMITATIONS AND FUTURE RESEARCH

Although our study provides valuable insights, it is not without limitations. Firstly, the data was collected through a survey prone to subjective bias, social desirability bias, and limitations in memory and insight. Secondly, our study employed a non-probabilistic sampling method tailored to capture insights from healthcare professionals with specific experiences and access to ICT. However, this approach limits the generalizability of our findings. Consequently, our conclusions can be cautiously extended only to similar populations with comparable characteristics. Even though we adopted countermeasures to curb such perception biases, we understand that larger sample sizes would help overcome such issues and allow more robust inferences. We acknowledge that using the name of the technology to assess its adoption levels of ICTs may not yield the same depth of detail as a domain-specific application study. However, to limit the possibility of obscuring details, the survey instrument included concise descriptions of each technology, helping participants accurately associate their work with the designated main technology.

Considering that our results showed an overall non-influential effect of the adoption of ICTs on performance and competence on the level of adoption of digital technologies, we may need further exploration of competence and organizational performance evaluation studies. As technology advances, it is essential to consider more detailed and specific applications tailored to the specific needs of hospitals. Additionally, it is essential to evaluate the long-term performance outcomes of these technologies through a longitudinal study and take them into account for future research. This will help ensure that hospitals are able to make informed decisions when implementing new technologies. Additionally, a set of related potential future research opportunities is identified. First, to examine the mediating role played by individual, group and organization-level organizational learning capabilities of the association between ICTs and operational performance. Secondly, it is important to conduct an in-depth study on the impact of digitalization in healthcare organizations which focus on operational outcomes such as efficiency, productivity, resource utilization, cost control, patient flow, quality of care, and data management. Additionally, the study should evaluate stakeholder-based outcomes such as patient experience, physician, clinician, and nursing staff satisfaction, administrative staff satisfaction, hospital leadership and management satisfaction, regulatory compliance and accreditation, community and public perception, and effective external collaborations. Thirdly, to examine the role of ICTs in addressing health disparities and improving healthcare accessibility among diverse populations by investigating barriers and facilitators of technology adoption in underserved communities. Fourth, to assess the evolving regulatory landscape in healthcare and its influence on H4.0 adoption by investigating the compliance challenges faced by organizations and the role of regulatory frameworks in shaping digital strategies. Finally, to study the impact of training programs, educational interventions, and academic collaborations on healthcare workforce readiness for digital transformation by assessing how training influences competence and ICT adoption rates.

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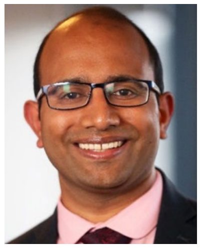

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