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EVALUATING READINESS FOR DIGITAL AND AI TECHNOLOGY INTEGRATION TO ADOPT INDUSTRY 4.0 AND ITS EFFECT ON PRODUCTIVITY IN PUBLIC SECTOR HEALTHCARE OPERATIONS: A QUANTITATIVE ANALYSIS

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Abstract

Background: *This quantitative study uses the Organizational Readiness for Change (ORC) theory and the Technology Acceptance Model (TAM) to assess how prepared the public sector healthcare systems in Gujranwala are to integrate digital and AI technologies and what effects this will have on productivity. Digital and AI technologies have the potential to revolutionize healthcare, but adoption in the public sector is hampered by issues like worker preparedness, resource limitations, and legal barriers.*

Methodology: *Data is gathered from management, IT, and healthcare workers in two public healthcare facilities using standardized questionnaires. Descriptive statistics, reliability evaluations, and correlation analyses are used in the analytic process.*

Results: *The results show that respondents have a favorable attitude towards adopting technology, with levels of preparedness ranging from moderate to high. The acceptability of technology is significantly influenced by organizational readiness, highlighting the need of leadership.*

Conclusion: *The study's implications underscore the necessity of tackling perceived obstacles, cultivating leadership backing, and advocating for cooperation to augment technology integration in public healthcare. Suggestions encompass allocating funds for resources and educational initiatives, involving leaders, and establishing a supportive atmosphere for novelty. A small sample size and a concentration on quantitative analysis are two limitations that point to potential directions for future research. These include qualitative and longitudinal methods to gain a deeper understanding of the dynamics of technology adoption and the efficacy of interventions in public sector healthcare settings.*

INTRODUCTION

The combination of digital and artificial intelligence (AI) technology has emerged as a disruptive force in the healthcare industry (Păvăloaia & Necula, 2023). This integration has the potential to greatly improve efficiency, elevate patient care, and guide decision-making that is driven by data (Zewail & Saber, 2023). For example, artificial intelligence-assisted diagnostics and robotic surgery are only two examples of how the digital revolution is poised to change healthcare delivery (Vercauteren, Unberath, Padoy & Navab, 2019). Electronic health records (EHRs) and telemedicine are also examples. On the other hand, the readiness of healthcare systems in the public sector to accept and fully utilize modern technologies continues to be a complex task (Aarons, Hurlburt & Horwitz, 2011).

Public healthcare systems around the world are under increasing constraints, such as rising healthcare expenses, an aging population, and an increasing burden of chronic diseases (Laprise, 2023). The implementation of digital and artificial intelligence technology is a solution that shows promise. Wearable technology and mobile health applications are examples of digital health solutions that make it possible to remotely monitor patients, create individualized treatment regimens, and increase patient participation (Chen, Ding, & Wang, 2023). The use of artificial intelligence-driven predictive analytics helps in the early detection of diseases and the planning of treatments, while robotic surgery technologies improve precision. In addition, artificial intelligence algorithms for medical image processing have the potential to greatly improve both the accuracy and performance of diagnostic procedures (Yagi,Yamanouchi, Fujita, Funao & Ebata, 2023).

However, the adoption of technology in the public sector healthcare sector is hampered by a number of factors, including limited financial resources, inadequate worker readiness, regulatory obstacles, and reluctance to change (Torvinen & Jansson, 2023). Despite the fact that ensuring that healthcare personnel are proficient in the utilization of these technologies continues to be a priority, limited finances frequently divert resources away from investments in technology at the same time. It is vital to address concerns around job displacement and data privacy in order to overcome opposition to change. Regulatory frameworks need to evolve in order to keep up with the rapid advancements in technology (Babu, 2024).

It is essential to have a comprehensive grasp of preparedness variables in order to realize the full potential of digital and artificial intelligence technologies in the public sector healthcare sector. In order to shed light on both the challenges and the potential that exist within public healthcare systems, the purpose of this research is to investigate the current state of preparation for integrating digital and artificial intelligence technologies. In the following sections, we will delve into key readiness factors, investigate successful case studies, and provide recommendations about how to nurture a healthcare landscape that is more technologically advanced and focused on the patient.

The purpose of this study is to conduct a quantitative analysis of the existing state of preparation in public healthcare sectors, with the goal of identifying areas of weakness and opportunities for enhancement.

Literature Review:

In recent years, the incorporation of digital and artificial intelligence (AI) technology into the healthcare industry has attracted a significant amount of attention due to the fact that it has the potential to revolutionize the respective industry (Ali, Abdelbaki, Shrestha, Elbasi, Alryalat, & Dwivedi, 2023).

It is important to note that electronic health records, often known as EHRs, have been the primary focus of digitalization initiatives. The HITECH Act has been shown to have a significant impact on the adoption of electronic health records (EHRs) in the United States, as demonstrated by studies such as Adler-Milstein and Jha (2016). Electronic health records (EHRs) simplify the management of patient data, cut down on errors, and improve information accessibility, all of which contribute to an improvement in patient care and administrative efficiency.

The diagnostic tools that are powered by artificial intelligence have shown outstanding capabilities. The application of deep learning algorithms, in particular, has demonstrated potential in the field of disease identification and medical image analysis. Topol's book "Deep Medicine" (2019) highlights the ways in which artificial intelligence might improve diagnostic accuracy, which will ultimately lead to better outcomes for patients.

The use of digital health solutions has also become increasingly popular in the areas of patient interaction and remote monitoring. Wearable technology and mobile health applications make it possible for individuals to take an active role in the administration of their own healthcare treatment. The utilization of these technologies enables real-time monitoring of vital signs, adherence to medicine, and lifestyle choices, which ultimately results in improved self-care and better early intervention (Chen, Ding & Wang, 2023).

On the other hand, the readiness of healthcare systems in the public sector to adopt new technology varies greatly. There is a socio-technical model that Sittig and Singh (2016) suggest for the purpose of researching health information technology readiness. This model emphasizes the significance of taking into account organizational and cultural aspects.

In public healthcare systems, the presence of financial restraints is a key hurdle that restricts the amount of money that can be invested in technology. In addition, readiness of the workforce continues to be an issue. Professionals in the healthcare industry require training in order to fully utilize the potential offered by digital and artificial intelligence technology. Additionally, issues regarding job displacement demand careful attention (Lambert, Madi, Sopka, Lenes, Stange, Buszello, & Stephan, 2023).

Regulatory frameworks frequently lag behind technology changes, which creates difficulties for regulations to comply with. The adoption of technology is further complicated by the resistance to change that exists within healthcare institutions. This resistance is generated by cultural factors and worries about the privacy of data (Nguyen & Tran, 2023).

Research Questions:

1. What is the current level of readiness among public sector healthcare systems for adopting digital and AI technologies?
2. What are the main barriers to the integration of these technologies in public healthcare operations?

Research Objectives:

- To quantitatively measure by using a questionnaire, the readiness of public sector healthcare systems for digital and AI technology integration.
- To find the hurdles which Public health care sector might face during digitalization

Theoretical Framework:

The Technology Acceptance Model and the Organizational Readiness for Change (ORC) theory will serve as the guiding principles for the research project that will investigate the incorporation of digital and artificial intelligence technologies in the healthcare industry, particularly within public sector healthcare systems. These frameworks provide a solid foundation for comprehending the intricate dynamics that are at play, offering vital insights on the organization's readiness to make technological changes and the degree to which it is willing to accept technological advancements. (Davis, 1989).

Technology Acceptance Model (TAM):

The Technology Acceptance Model, initially developed by Davis in 1989, is widely recognized and applied in the context of technology adoption and acceptance. TAM posits that a user's intention to use a technology is influenced by two primary factors: perceived ease of use and perceived usefulness. Perceived ease of use reflects the extent to which individuals believe that using the technology will be effortless, while perceived usefulness pertains to the degree to which individuals perceive that the technology will enhance their performance or productivity (Davis, 1989).

In the context of our study, TAM will help in assessing healthcare professionals' and administrators' perceptions of digital and AI technologies' ease of use and their perceived usefulness in improving patient care and healthcare operations. By exploring these factors, the study can gain insights into the willingness and intention of healthcare professionals to adopt and embrace these technologies.

Organizational Readiness for Change (ORC) Theory:

The Organizational Readiness for Change theory, proposed by Armenakis and Harris (2009), focuses on the readiness of organizations to initiate and successfully implement change initiatives. It emphasizes the importance of multiple dimensions, including leadership support, resources, and employee commitment, in determining an organization's readiness for change. ORC theory recognizes that successful technology adoption is contingent on the organization's preparedness and ability to support the change process.

In our study, ORC theory will be instrumental in assessing the public sector healthcare system's readiness to embrace digital and AI technologies. It

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will explore critical factors such as leadership support for technology adoption, the availability of necessary resources, and the organization's capacity to provide training and support for healthcare professionals. By applying ORC theory, the study aims to identify areas where organizational readiness may be lacking and recommend strategies to enhance the healthcare system's capacity to effectively implement technological changes. (Weiner, B. J. 2020).

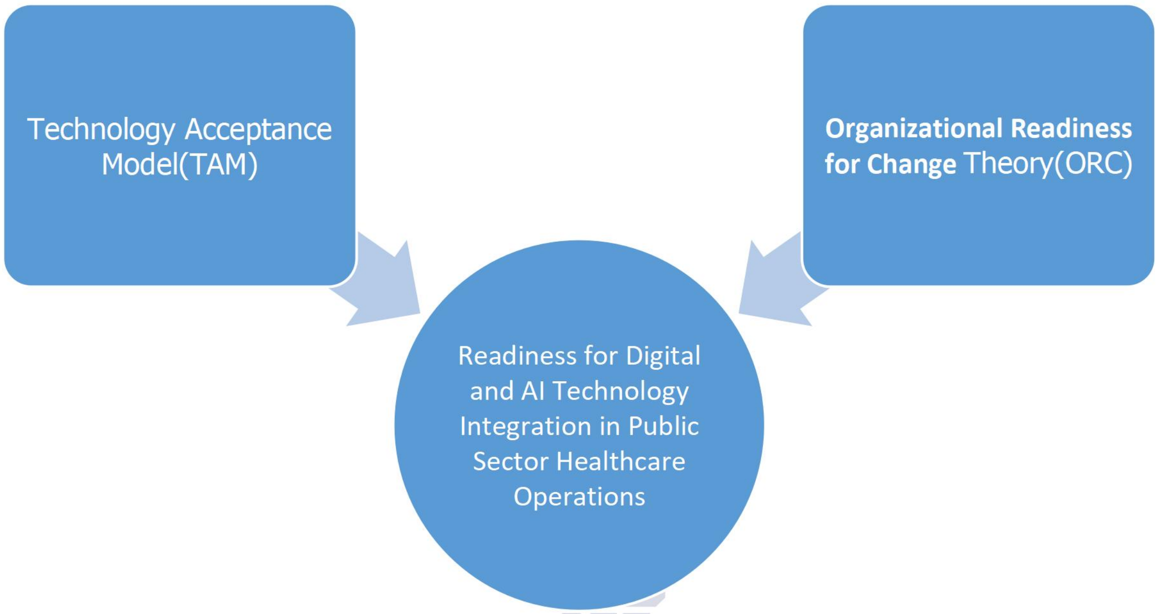

Fig 6.1 Relationship between TAM and ORC with Readiness for Digital and AI Technology Integration in Public Sector Healthcare Operations

Hypothesis: The health sector has shown comparatively good digital readiness level and able to overcome barriers to adopting digital and AI technologies.

Sample & Population:

The study was conducted by the targeting a sample of 120 of healthcare professionals, IT staff, and management personnel from two public healthcare institutions in Gujranwala. A stratified sampling technique was used to ensure representation across different regions and institution sizes.

Instrumentation & Measures

Data was collected through a structured questionnaire, including Likert-scale questions to measure variables related to technology acceptance, organizational readiness, and perceived barriers to technology adoption. The questionnaire's validity and reliability will be ensured through pilot testing and expert reviews.

Results

This study focused on the partial least square structural equation modeling (PLS-SEM) technique and examined variables and hypotheses using Smart PLS-4 statistical software. The program is regarded as a contemporary measurement tool with a trustworthy estimate technique and is widely utilized in research (Ali et al. 2018; Ringle et al. 2005).

According to Hair et al. (2016), PLS-SEM is a well-liked option because of its simplicity and low data needs. Results Table 1 shows the study's descriptive statistics and inter-correlations of variables. An examination of this Table shows that demographic variables including gender, age, and educational level male respondent were 69 (55.6%), female respondent were 41.10%, the respondents age from 20 to 30 years old were 24 (19.66%), 31-40 years response rate was 51 (41.1%) and 41 to 50 were 37

(29.8%) response rate from 50+ years old was 12(9.7%). The respondent response rate according to education level Matric 3(2.4%), Intermediate 22(17.7%), Bachelor 54 (43.5%) and Master 45(36.3%).

Table 1: Demographic

Constructs	Classification	Frequency	Percentages
Gender	Male	69	55.6%
	Female	51	41.1%
Age	20-30	24	19.66%
	31-40	51	41.1%
	41-50	37	29.8%
	Above 50	12	9.7%
Education	Matric	3	2.4%
	Intermediate	22	17.7%
	Bachelor	54	43.5%
	Master	45	36.3%

Descriptive statistics (see Table 2) aid in understanding the scope and characteristics of the variables under consideration in the study. The "N" column shows the number of observations for each construct. There are 124 observations or responses for each of the four constructs. The "mean" value represents the average or arithmetic mean values for each construct. It represents the dataset's core trend. Similarly, the average value for "TAM" was 4.06, "OR" was 3.99, "PBTA" was 3.74 and “DREP” 3.81. The "Std. deviation" measures the data's dispersion or variability around the mean. A higher standard deviation indicates greater variability in the scores. Additionally, the SD for the “TAM” was 0.68, “OR” was 0.78, “PBTA” was 0.91 and for “DREP” was 1.07.

Table 2: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
TAM	124	1	5	4.06	0..679
OR	124	1	5	3.99	0.766
PBTA	124	1	5	3.74	0.915
DREP	124	1	5	3.81	1.074

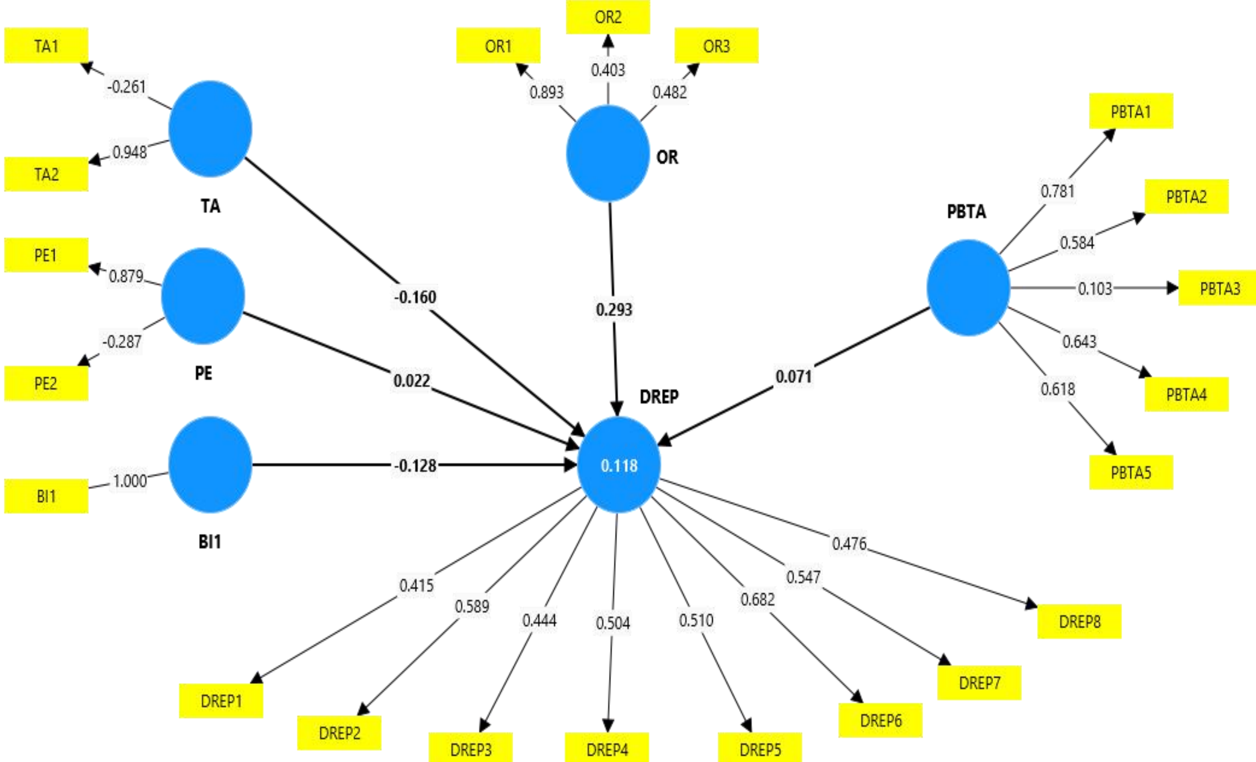

Figure1: Measurement model assessment

Table 3: Correlation analysis is an important first step in establishing the level of relationship between two categorical variables as illustrated below:-

Table 3: Correlation Analysis

	BI1	DREP	OR	PBTA	PE	TA
BI1	1.000	-0.041	0.220	0.048	-0.116	-0.139
DREP	-0.041	1.000	0.274	0.169	0.050	-0.119
OR	0.220	0.274	1.000	0.320	0.044	0.092
PBTA	0.048	0.169	0.320	1.000	0.063	-0.055
PE	-0.116	0.050	0.044	0.063	1.000	0.027
TA	-0.139	-0.119	0.092	-0.055	0.027	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation analysis in Table 3 elucidates relationships among categorical variables: Behavior Intentions BI1, DREP, OR, PBTA, PE, and TA. Generally, weak to moderate correlations are evident. BI1 exhibits weak positive correlations with OR and PBTA but weak negative correlations with DREP, PE, and TA. DREP demonstrates moderate positive correlations with OR and PBTA, alongside weak positive correlations with BI1 and PE. OR displays moderate positive correlations with DREP and PBTA, and weak positive correlations with BI1 and PE. PBTA indicates moderate positive correlations with OR and weak positive correlations with DREP, BI1, and PE. PE shows weak negative correlations with BI1 and TA, and weak positive correlations with DREP, OR, PBTA, and TA. TA reveals weak negative correlations with BI1 and DREP, weak positive correlations with OR, PE, and a moderate negative correlation with PBTA. These findings illuminate the interconnected nature of these variables, facilitating further analysis and decision-making processes.

Table 4: Convergent validity

Constructs	Items	Loading	Alpha	CR	AVE
Technology Acceptance Model (TAM)	TA1	-0.261	0.340	0.500	0.500
	TA2	0.948			
	PE1	0.879			
	PE2	-0.287			
	BI1	1.00			
Organization Readiness for Change (ORC)	ORC1	0.893	0.337	0.637	0.398
	ORC2	0.403			
	ORC3	0.482			
Perceived Barriers to Technology Adoption (PBAT)	PBAT1	0.781	0.605	0.697	0.352
	PBAT2	0.584			
	PBAT3	0.103			
	PBAT4	0.643			
	PBAT5	0.618			
Digital Readiness Employee Performance (DREP)	DLEP1	0.415	0.626	0.750	0.278
	DLEP2	0.589			
	DLEP3	0.444			
	DLEP4	0.504			
	DLEP5	0.510			
	DLEP6	0.682			
	DLEP7	0.547			
	DLEP8	0.476			

Table 4 provides information on convergent validity, indicating the strength of the relationship between constructs and their respective items. The constructs include Technology Acceptance Model (TAM), Organization Readiness for change (ORC), Perceived Barriers to Technology Adoption (PBAT), and Digital Readiness Employee Performance (DREP).
The information given describes how constructions and the components that make them up have convergent validity. TA1, PE1, PE2, and BI1 have designated loadings for the Technology Acceptance Model (TAM), while TA1 has a negative loading. Low alpha, composite reliability (CR), and average variance extracted (AVE) are displayed by the construct. The ORC (Organization Readiness for change) consists of ORC1, ORC2, and ORC3, with ORC1 having comparatively larger loadings. PBAT is made up of PBAT1 through PBAT5, with most products showing modest loadings. DLEP1 through DLEP8 are listed in Digital Readiness Employee Performance (DREP), with different loadings for each item. Overall, these insights are essential for verifying the accuracy and reliability of the measurement model in the study, even though some constructs show greater reliability measures than others.

Discriminant validity:

The Heterotrait-Monotrait ratio was used to assess discriminant validity (see Table 5), and the results showed that each construct's value was less than 0.85, indicating significance, as shown in Table 5 (Kline 2015). The findings confirmed that the HTMT ratio of built items was valid (Kline 2015). Overall, this study used convergent and discriminant methods to evaluate the validity and reliability of the measurement model. The results suggested that the model had acceptable validity and reliability indicators (Hair et al. 2017, 2014; Cheung & Wang 2017; Kline 2015).

Table 5 presents Heterotrait-Monotrait (HTMT) ratios, crucial for assessing discriminant validity between constructs. The ratios compare inter-construct relationships against intra-construct relationships. While specific ratios for Behavioral Intention (BI1) aren't provided, its weaker relationships with other constructs are evident. For instance, the ratio between Digital Readiness Employee Performance (DREP) and BI1 is modest at 0.059. Conversely, Organizational Readiness (OR) and Perceived Barriers to Technology Adoption (PBTA) display stronger relationships, with OR ratios of 0.285 with BI1 and 0.592 with DREP, and PBTA's notable 0.815 ratio with OR. Technological Adoption (TA) notably exhibits high ratios, particularly with Profit Efficiency (PE) at 1.853, indicating significant positive relationships which means they have good adoption to new technology. These findings stress the importance of discerning between constructs to validate the measurement model used.

Tab le 5: HTMT

	BI1	DREP	OR	PBTA	PE	TA
BI1						
DREP	0.059					
OR	0.285	0.592				
PBTA	0.080	0.336	0.815			
PE	0.458	0.302	0.526	0.444		
TA	0.781	0.764	0.684	0.757	1.853	

7. Discussion:

The findings of this study shed light on the readiness of public sector healthcare systems in Gujranwala for the integration of digital and AI technologies, and their implications for productivity. The discussion revolves around several key themes derived from the research objectives, theoretical framework, and results obtained through quantitative analysis.

Readiness for Technology Integration:

The goal of the study was to assess how prepared public healthcare systems were at the moment to use digital and artificial intelligence (AI) technology. According to their favorable opinions of the benefits and use of technology, respondents demonstrated a moderate to high degree of preparedness, as indicated by the results. This shows that Gujranwala's management team, IT workers, and medical professionals are aware of the potential advantages of technology integration for enhancing patient care and operational effectiveness. Being prepared in this way is essential to creating an atmosphere that is favorable to the adoption and successful use of technology.

Key Barriers to Integration:

Although there is a general inclination towards the adoption of technology, the study has identified certain obstacles that may impede the smooth incorporation of digital and artificial intelligence technologies in public sector healthcare operations. These obstacles include a lack of funding or resources for implementing technology, employee resistance to change, a lack of competent technical assistance, worries about data security and privacy, and a misalignment of organizational objectives with technology. These results highlight the variety of obstacles that healthcare organizations may encounter on their path to digital transformation. In order to successfully implement technology in healthcare settings and overcome reluctance to change, it is imperative that these obstacles be addressed.

Implications for Practice:

The study's conclusions have significant practical ramifications, especially when it comes to managing healthcare in the public sector. First and foremost, funding for IT infrastructure and resources needs to be prioritized by legislators and executives in the healthcare industry. This entails setting aside enough money in the budget for the adoption of new technology, offering thorough staff training and support, and improving technical help and troubleshooting systems. Furthermore, overcoming change resistance and encouraging the adoption of digital and AI technologies inside healthcare organizations requires cultivating a culture of creativity and collaboration.

Furthermore, to ensure the efficiency and durability of technological efforts, they must be in line with organizational priorities and goals. Strategic plans integrating technology into the whole operational framework of healthcare institutions are necessary to improve patient care, increase operational efficiency, and accomplish organizational goals. Furthermore, resolving privacy and data security issues is critical to gaining stakeholders' trust and confidence. Strong data protection policies and compliance frameworks should be put in place by healthcare organizations to protect patient data and reduce privacy concerns brought on by technology use.

Limitations and Future Directions:

This study has limitations even if it offers insightful information about the state of public sector healthcare operations' preparedness for integrating digital and AI technologies. The very small sample size and emphasis on quantitative analysis are two limitations that could restrict how far the results can be applied. Larger sample numbers and a mixed-methods approach, involving qualitative data, could be beneficial for future study in order to provide deeper insights into the intricacies of technology adoption in healthcare settings. Furthermore, longitudinal studies could monitor the advancement of technological efforts over time and evaluate their long-term effects on patient outcomes and productivity.

In conclusion, by assessing the preparedness of public sector healthcare systems for technological integration, this study adds to the expanding body of research on digital transformation in healthcare. Through the identification of significant obstacles and practical implications, the study provides insightful guidance for healthcare executives and policymakers in navigating the opportunities and problems related to technology adoption. In the end, utilizing the full potential of digital and AI technologies to enhance patient care and operational efficiency in public sector healthcare settings requires cultivating a culture of innovation and cooperation.

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