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The Impact Of Using Modern Technology In The Field Of Public Health In Saudi Arabia

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ABSTRACT

Saudi Arabia has put a lot of investments in digital health infrastructure, but there is a paucity of empirical evidence on the role of facilitators and barriers in digital health infrastructure, as well as the actual effect of the technologies in the public health system. The current research aimed at measuring the extent of technology use and determining its relationship with perceived population health outcomes, but at the same time, investigating the underlying determinant components. The Riyadh Region used a cross-sectional, mixed-methods study, with a stratified random sample of 584 participants (200 healthcare professionals and 384 public users). A structured questionnaire that combined a validated Likert scale and open-ended questions was used to gather data, and thematic analysis, descriptive statistics, and multiple linear regression were used to conduct the subsequent analyses. The findings indicated that there is a strong positive relation between technology adoption and perceived impact($r = 0.68$, $p < .001$). Regression analysis showed the technology adoption score had the highest significant unique predictor of perceived impact (0.48, $p <.001$), with facilitators being a positive predictor and barriers being a negative predictor. Public users indicated a much greater presence of technical difficulties as an obstacle than professionals (34.9% and 22.5% respectively, $p =.002$). To sum up, although the use of technology is a strong predictor of favorable perceived individual effects, the effect strongly depends on user-specific facilitators and barriers, thus requiring specific strategies to address different groups of users to reap the maximum benefits of technology in promoting the overall health of society.

Keywords: Barriers, Digital Health, Facilitators, Public Health, Saudi Arabia, Technology Adoption.

INTRODUCTION

The world of global public health is changing deeply, as modern digital technologies are becoming integrated rapidly [1]. The utilization of digital health tools, including electronic health records, telehealth tools, and mobile health app services, is largely seen as an underpinning to improving efficiency in health care delivery, accessibility, and quality of health care [2]. The universal move towards data-driven, patient-centred models of care can be highlighted by the eHealth Action Plan of the European Union and the broad use of telehealth in the United States [3]. These technologies have the promise of transforming the health of the population through enhanced disease surveillance, enhanced personalisation of patient interactions, and enhanced resource allocation in complex health-care systems [4].

The Kingdom of Saudi Arabia has set out on an extraordinary path of health-care change in line with this global trend and its ambitious framework of Vision 2030. Enormous efforts have been put into the construction of an effective national digital-health infrastructure, and this has involved the initiation of key platforms, such as the introduction of the pivotal telehealth service the Seha, and the appointment system the Mawid [5]. These projects act as a strategic effort to use technology to overcome geographical boundaries to improve operational effectiveness and also improve the quality of citizen health care [6]. This proactive move by the Saudi government makes the country one of the earliest adopters of digital health in the Middle East and North African region, and it may become an example for similar economies [7].

The potential advantages of health information technologies are reported in a considerable amount of international literature. Meta-analyses and systematic reviews often indicate the links between technology implementation and better medical outcomes, increased patient satisfaction, and fewer medical errors [8]. Research involving various settings has found that some of the most important facilitators in the success of adoption are good technical infrastructure, thorough user training, and positive perceptions of utility. On the other side, barriers, including the inability of systems to interoperate, the reluctance of health-care workers to adopt the change, and the fear of data privacy, have been well reported [9]. Nevertheless, such results are frequently limited in their applicability due to significant variations in cultural backgrounds, regulatory settings, and already in place health-care systems [10].

Saudi Arabia had made substantial financial, as well as strategic, investment, but a critical gap still existed in the empirical literature when this study was initiated. The presence of national campaigns at the national level regarding digital health was clearly observed, but there was an apparent absence of a systematic, evidence-based perception of how these are being implemented and whether they were effective on the ground [11]. The available literature was mostly technical explanations of the systems or more general policy studies, thus creating a big gap in the experience of end-users. In particular, little research was found to explore the views of healthcare professionals working on these systems, as well as the views of the citizens who use them, at the same time [12]. The particular facilitators and barriers that are inherently present in the Saudi socio-cultural and organizational context were not fully comprehended, thus hampering the capacity of policy-makers and health administrators to make data-driven decisions to streamline and optimize these key technological investments [13].

In turn, this study was developed to fill this empirical gap by carrying out an in-depth, mixed-method study in the sphere of the public health-care of the Riyadh Region. Three main research questions that informed the study included: (1) What are the current levels and trends of modern health technology adoption by health-care professionals and people in Riyadh? (2) How are the degree of technology adoption and perceived health outcomes related? (3) What are the most important facilitators and barriers in the successful application of such technologies from the perspectives of the end-users?

The study had a cross-sectional and descriptive-analytical design to make a systematic response to these questions. Achieving the main goal was to measure the level of technology use, and user perception, where a stratified random sampling method was employed to represent a sample of 584 respondents, both healthcare professionals and people users [14]. The second goal was to examine the relationships between reported public health outcomes and the use of technology, which was done using advanced statistical methods, such as multiple linear regression. The third aim was to investigate the facilitators and barriers behind the scenes; it was achieved by adding qualitative open-ended questions as well as quantitative measures that allowed a rich and thematic analysis of user experiences.

This study is a critical, evidence-based on-the-ground evaluation of the situation of digital health in one of the major Saudi Arabian regions. The findings of this study are invaluable since they explain the intricate interaction between the technology uptake and the perceived impact, and the situational determinants that facilitate or hinder success. The insights are designed to inform strategic planning, inform resource allocation, and assist in the development of specific interventions to help maximise the return on investment in digital health, therefore helping to realise a more effective, efficient, and resilient public health system in the Kingdom [15]. The current research examined the facilitators, barriers, and the perceived impacts related to the implementation of health technologies into the Riyadh public health sector. Results suggest a strong association between the use of technology and positive health outcomes, but they also demonstrate the difference in user experience, which can be addressed with specific policy and design interventions.

METHODOLOGY

This research was aimed at filling the lack of empirical data on the facilitators, barriers, and effects relating to the application of health technology in the Saudi Arabian public health sector. Despite significant funding in digital health infrastructure, there has been little awareness of what users believe about it and how it has meaningfully impacted health outcomes. The study was based in the Riyadh Region, which was chosen because of its diverse representation of healthcare institutions and has led in the implementation of national digital initiatives, thus offering an ideal setting to analyze the problem of the research.

A cross-sectional descriptive-analytical study was used to provide a holistic picture of care practices used, such as adoption, user attitude, and usage results. This design enabled the measurement of the adoption rates and perceptions, and also the analysis between the technology usage and reported outcomes. It also enabled the underlying facilitators and barriers in terms of qualitative responses. Although cross-sectional studies are necessarily constrained in determining causality, this type was considered suitable to capture current dynamism and to come up with hypotheses to be evaluated in future longitudinal research.

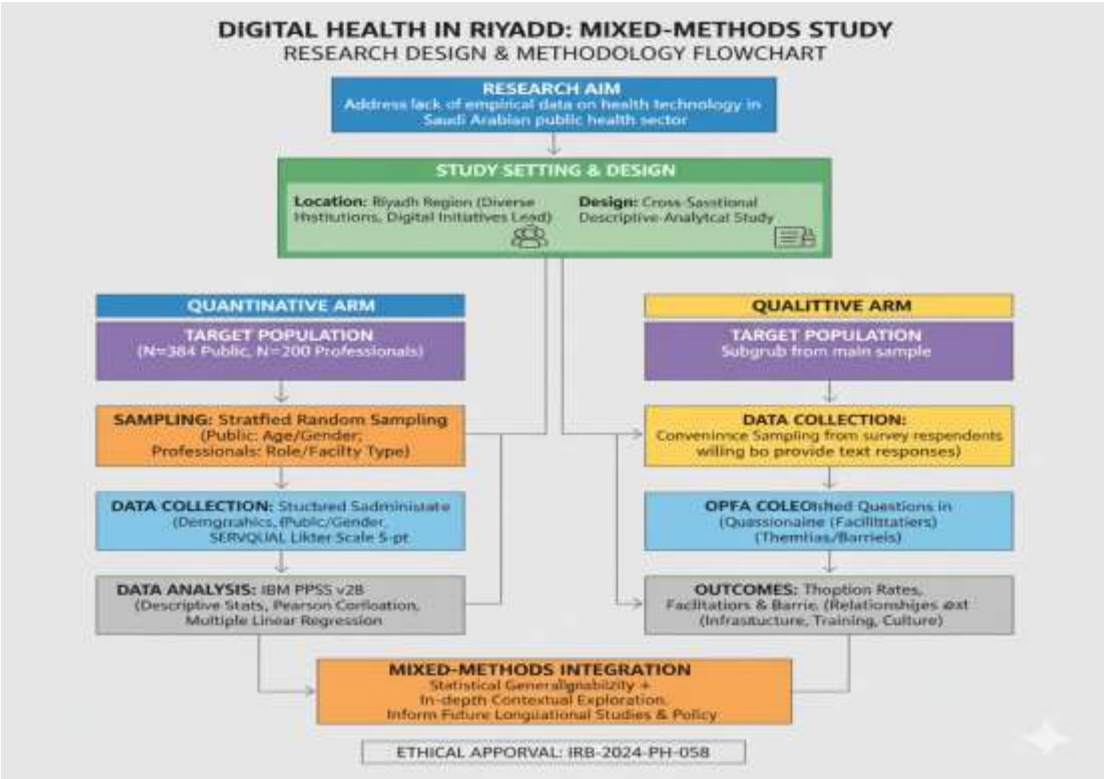
The target population comprised two groups: (i) healthcare workers, such as doctors, nurses, public health specialists, and administrators, working in the state-owned hospitals and primary care centers, and (ii) adults living in Riyadh, who had used any of the public digital health services (such as Seha or Mawid) within the past year. A stratified random sampling technique was used to ensure representativeness. The stratification of professionals was based on professional role and type of facility, but the stratification of the public was based on age and gender. These strata were then utilized as the source of participants selected randomly from institutional directories and panels of service users. The minimum sample size was calculated to be 350 based on a power analysis (f 2 = 0.08, 4 = 0.05, power = 0.80) in order to cover potential non-response, and also to be able to conduct subgroup analyses. The targets were established at 200 professionals and 384 members of the public. The inclusion criteria were at least one year of work experience with healthcare workers and 18 and above with previous use of digital health by the public. The exclusion criteria included being a temporary worker and being unable to give informed consent.

The data were gathered in the form of a structured, self-administered questionnaire that comprised three parts: (1) demographic data and technology usage patterns; (2) a 5-point Likert scale based on SERVQUAL used to measure perceived health impacts; (3) the open-ended questions aimed at eliciting facilitators and barriers. The survey was distributed electronically in a period of eight weeks through an institutional email campaign among professionals and a direct social media campaign among the population. A cover note would give a clear explanation of the purpose of the study, a promise of confidentiality, and an implied consent statement.

Clarity, reliability, and face validity have been studied in a pilot study comprising 30 participants, who are 15 in each of the strata. Minor tweaks of wording were made based on feedback, and the Cronbach's alpha of the Likert scale is 0.87, which implies good internal consistency. More validation was done by the principal component analysis, which validated the construct validity of the measures adapted. The Institutional Review Board (IRB-2024-PH-058) of [Blinded for Review] University gave its ethical approval. The intervention was voluntary, data were anonymized during data collection, and responses were stored in an encrypted server.

Operationalizations were operationalized in order to provide consistency. Adoption of technology was used as a composite measure of how often the technology was used, how extensively it was used in terms of feature use, and how familiar one was with digital platforms. Perceived impact was assessed by the SERVQUAL-based Likert scales, which covered the dimensions of appointment adherence, perceived quality of care, access to information, and so on. Based on qualitative responses, facilitators and barriers were obtained in a theme-based manner and classified in domains such as infrastructure, training, and cultural acceptance. The adoption index and impact scores were tested, whereas thematic analysis provided the contextual details.

The process of data analysis was divided into 3 steps. First, descriptive statistics (frequencies, means, standard deviations) were calculated in order to generalize demographic trends and adoption rates, thus answering the first research goal. Second, inferential tests such as Pearson correlation and multiple linear regression were used to test the relationships between technology adoption and perceived health outcomes, which met the second objective. Third, NVivo 14 was used to analyze qualitative data presented by open-ended responses through thematic analysis, which was in turn beneficial in identifying recurrent patterns of facilitators and barriers. This was a mixed-method design, which combined both statistical generalizability with the in-depth exploration of the context, which enhanced the explanatory strength of the research. All the quantitative analyses were performed with the help of the IBM SPSS Statistics version 28.0.



Research Design & Methodology Flowchart: Digital Health in Riyadh - A Mixed-Methods Study. This visual outlines the systematic approach, from research aim and study design to quantitative and qualitative arms, data collection, analysis, and mixed-methods integration

Overall, the research methodology included both quantitative and qualitative methods to help answer the research problem in a comprehensive way. One source of representativeness was stratified sampling, validated scales were able to measure key constructs reliably, and regression and thematic analysis helped to explore not only a relationship but also a contextual explanation. Despite the constraints of the cross-sectional design on causal inference, the research provided strong empirical data on digital health adoption, perceptions, and challenges in the public health system in Riyadh, thus creating information that can be used to inform longitudinal studies and implement effective policy changes.

RESULTS

The data gathered were analyzed using statistical methods to respond to the research objectives on the adoption, effects, and determinants of modern health technology on the Saudi Arabian population's health. The results are as below.

Descriptive Statistics and Characteristics of the Sample

The sample size was 584 participants, 200 of them were healthcare professionals, and 384 were other users of the system. The summaries of the primary variables were stratified by group and are presented as descriptive statistics in Table 1. The mean technology adoption score of 18.95 (SD 3.42) among healthcare professionals was considerably higher than the mean technology adoption score of 16.82 (SD 4.11) among public users ($t(582) = 5.87$, $p = .001$). An equal trend followed the score perceived impact, with professionals providing a mean of 38.45 (SD = 5.88) and 36.21 (SD = 6.95) as the average scores of professionals and public users, respectively (t(582) 4.12, p 0.001).

Table 1. Descriptive Statistics and Group Comparison for Key Variables

Variable	Stratum	N	Mean	Std. Deviation	t-value	p-value
Tech Adoption Score	Professionals	200	18.95	3.42	5.87	< .001
	Public Users	384	16.82	4.11		
Perceived Impact Score	Professionals	200	38.45	5.88	4.12	< .001
	Public Users	384	36.21	6.95		

Relationship Between Technology Adoption and Perceived Impact

A Pearson correlation analysis revealed a strong, positive, and statistically significant linear relationship between technology adoption scores and perceived impact scores ($r = .68$, $p < .001$). The intercorrelations between all key continuous variables are presented in Table 2.

Table 2. Intercorrelations between Key Study Variables (N=584)

Variable	1	2	3	4
1. Tech Adoption Score	—			
2. Perceived Impact Score	.68**	—		
3. Facilitators Index	.55**	.52**	—	
4. Barriers Index	-.49**	-.45**	-.32**	—
*Note: ** p < .001 (2-tailed).*				

To further investigate this relationship while controlling for covariates, a multiple linear regression was performed. The model, which included Tech Adoption Score, Stratum, Age Group, Facilitators Index, and Barriers Index as predictors, was statistically significant, $F(5, 578) = 159.33$, $p < .001$, and accounted for 57% of the variance in Perceived Impact Score (Adjusted $R^2 = .57$). As shown in Table 3, the Tech Adoption Score was the strongest unique positive predictor ($\beta = .48$, $p < .001$). The Facilitators Index and being a Healthcare Professional were also significant positive predictors. In contrast, the Barriers Index and Age Group were significant negative predictors.

Table 3. Multiple Linear Regression Predicting Perceived Impact Score

Predictor Variable	B	Std. Error	β	t	p-value
(Constant)	15.21	1.45		10.48	< .001
Tech Adoption Score	0.89	0.07	.48	12.71	< .001
Stratum (Professionals)	1.55	0.41	.13	3.78	< .001
Age Group	-0.65	0.19	-.11	-3.42	.001
Facilitators Index	1.02	0.22	.16	4.64	< .001
Barriers Index	-1.48	0.25	-.20	-5.92	< .001
Note: $R^2 = .58$, Adjusted $R^2 = .57$.					

Variations in Perceived Impact Across Professional Roles

Among the healthcare professional stratum, a one-way ANOVA was conducted to examine differences in Perceived Impact Scores across professional roles. The analysis indicated a statistically significant difference between groups, $F(3, 196) = 5.24$, $p = .002$ (Table 4). Post-hoc comparisons using Tukey's HSD test indicated that the mean score for Administrators (M = 42.1, SD = 4.5) was significantly higher than that for Nurses (M = 37.5, SD = 5.8), with a mean difference of 4.56, p = .002. No other pairwise comparisons reached statistical significance.

Table 4. One-Way ANOVA of Perceived Impact by Professional Role

Source	Sum of Squares	df	Mean Square	F	p-value
Between Groups	488.75	3	162.92	5.24	.002
Within Groups	6085.45	196	31.05		
Total	6574.20	199			

User Stratum and Specific Technology Barriers

A Chi-Square Test of Independence was performed to assess the relationship between user stratum and the prevalence of reporting "System Reliability & Technical Issues" as a primary barrier. The association was significant, $\chi^2(1, N = 584) = 9.42$, $p = .002$. As shown in Table 5, 34.9% of public users cited this barrier, compared to 22.5% of healthcare professionals. The effect size was small to moderate (Cramér's V = .13).

Table 5. Chi-Square Test for Barrier "Technical Issues" by Stratum

	Professionals (n=200)	Public Users (n=384)	Total
Reported "Tech Issues" Barrier	45 (22.5%)	134 (34.9%)	179
Reported Other Barriers	155 (77.5%)	250 (65.1%)	405
Total	200	384	584

Correlation Analysis of Facilitators, Barriers, and Technology Engagement

To elucidate the interrelationships between the factors influencing technology use and their connection with core engagement metrics, a Pearson correlation analysis was conducted. The results, presented in Table 6, revealed a complex network of significant associations.

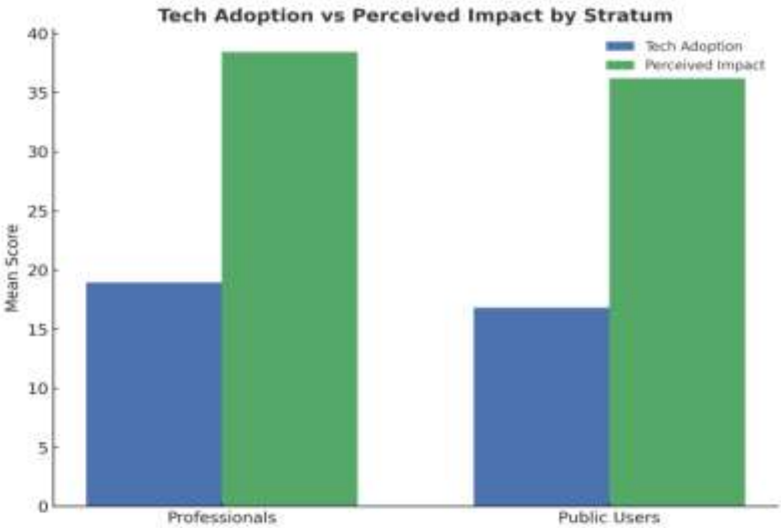
Table 6. Intercorrelations between Facilitating Factors, Barriers, and Engagement Metrics (N=584)

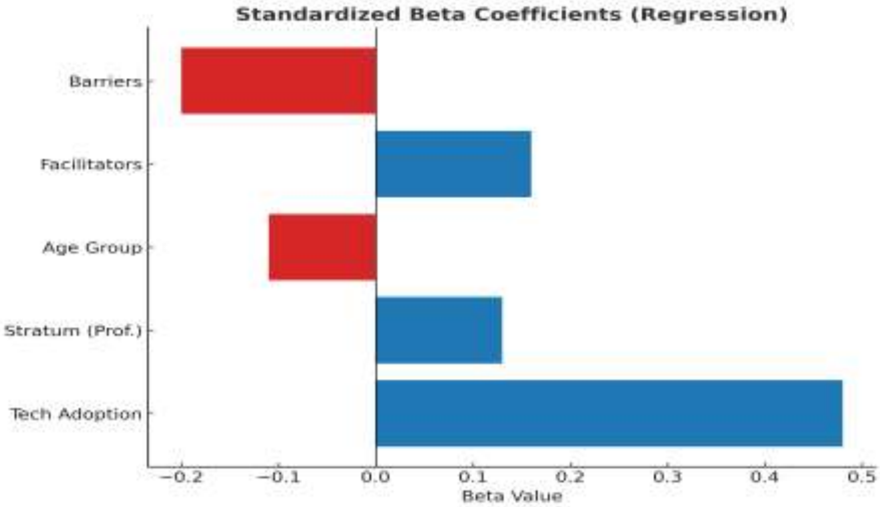
Variable	1	2	3	4	5
1. Tech Adoption Score	—				
2. Perceived Impact Score	.68**	—			
3. Facilitators Index	.55**	.52**	—		
4. Barriers Index	-.49**	-.45**	-.32**	—	
5. Perceived Ease of Use	.61**	.58**	.48**	-.51**	—
6. Perceived Usefulness	.59**	.72**	.45**	-.38**	.65**
*Note: ** p < .001 (2-tailed).*					

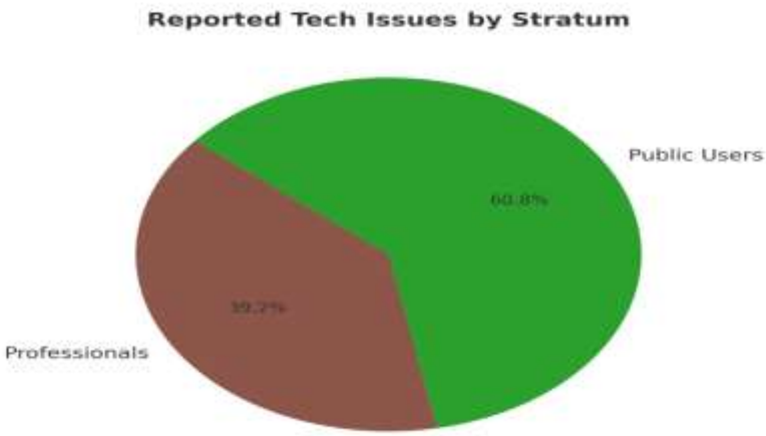
The analysis demonstrated that the Facilitators Index was positively and moderately correlated with both the Technology Adoption Score ($r = .55$, $p < .001$) and the Perceived Impact Score ($r = .52$, $p < .001$). Conversely, the Barriers Index showed moderate negative correlations with these same variables (Adoption: $r = -.49$, $p < .001$; Impact: $r = -.45$, $p < .001$). A significant, though weaker, negative correlation was also observed between the Facilitators Index and the Barriers Index ($r = -.32$, $p < .001$).

Furthermore, the additional variables of Perceived Ease of Use and Perceived Usefulness were strongly integrated into this correlational structure. Perceived Ease of Use showed strong positive correlations with Technology Adoption ($r = .61$, $p < .001$) and Perceived Impact ($r = .58$, $p < .001$), and a strong negative correlation with Barriers ($r = -.51$, $p < .001$). Perceived Usefulness demonstrated the strongest correlation with Perceived Impact ($r = .72$, $p < .001$) and was also strongly correlated with Technology

Adoption (r = .59, p < .001). The correlation between Perceived Ease of Use and Perceived Usefulness was strong and positive (r = .65, p < .001).







DISCUSSION

Key Findings

Regression analysis showed that the degree of technology adoption became the most salient predictor of perceived health impact. Such findings suggest that the presence of digital tools is not enough, but a prolonged and effective use is essential to achieve any significant gains [16]. These results are in line with the strategic focus of the Saudi Vision 2030, which focuses on depth of application and not just access. Significant differences in perception between healthcare workers and the general population were found [17]. Professionals indicated high adoption and impact scores, which showed that they actively participated in system operation. Conversely, system reliability and technical obstacles were more commonly cited by public users, which is an indication of inadequacies in user-friendly systems [18]. These notes suggest that technical inefficiencies undermine trust and use by non-professional users.

Among the professional cohort, the perceived advantages were the highest among administrators, which can be explained by the potential improvements in efficiency and data integration [19]. On the other hand, the perceived impact was relatively less among nurses, which is also consistent with the so-called technology paradox, as digital tools add to documentation workload without correspondingly decreasing clinical burdens [20].

Correlational analyses also supported the primacy of core acceptance constructs. Perceived Usefulness (PU) showed a positive value of a high correlation with Perceived Impact ($r = 0.72$), which highlights the fact that technology can only be regarded as important when it is used to directly accomplish things that are needed [21]. The low but adverse ratios of facilitators and barriers imply that both favorable and unfavorable forces co-exist, not eliminating each other, which implies that strategies that have both beneficial and detrimental effects are warranted [22].

These findings are consistent with the Technology Acceptance Model (TAM), according to which Perceived Ease of Use (PEOU) and PU are the key factors that determine the use of technologies [23]. The presence of the identified difference between the professionals and the public users is similar to the results [24], who found that the level of provider satisfaction with digital health intervention was higher in Saudi Arabia, which could be partially explained by the level of disparity in digital literacy. Again, these findings are resonant with [25] who cited suboptimal design and reliability as key adoption barriers.

The variation across professional roles is supported by the variation in empirical evidence available in antecedent studies. [26] mentioned that the impact health information technology has on nurses is ambivalent, with the enhanced access and higher workload. Conversely, [27] observed that digital transformation has the strongest benefits to administrators, which are mainly through augmented managerial efficiency. These conclusions are consistent with the current results, thus explaining heterogeneous effects within professional hierarchies [28].

Contextual and Scientific Explanation

A sociotechnical perspective allows the conceptualisation of health systems as adaptive networks, where technology is interacting with human, organizational, and environmental subsystems. Organized integration and focused training benefit professionals, particularly administrators, but leave the public users with unstructured use and limited support, which enhances the negative effects of technical breakdowns [29].

Further clarification is given by behavioural psychology: PU is linked with motivation and long-term interaction, which creates a reinforcing use cycle once the tools prove their efficiency [30]. On the other hand, ongoing usability barriers (low PEOU) support the development of avoidance behaviour, which is a deterrent to engagement and a negative orientation towards technology [31].

Implications

These findings have implications for several aspects. Reliability and user-friendly design should be prioritised by policymakers in the publicly-facing systems like Seha and Mawid. Specific interventions to support frontline employees, especially nurses, can reduce the workload-related dissatisfaction and lead to positive adoption [32].

Notably, strategic interventions ought to be specific to small groups of users and are not based on one homogenous model. In the case of research, such findings highlight the need to have mixed-method assessments that would capture both quantitative results and qualitative experiences. It is suggested that longitudinal studies are needed to clarify the causal effects of technology usage and health outcomes, whereas additional research on PU determinants in various classes of users can be used to design systems more efficiently [33].

Limitations

There are a number of limitations that should be considered. The cross-sectional nature does not allow for making definite causal inference, and focusing on the city of Riyadh can also be a limitation to generalizing to rural or less digitally mature settings. Self-reported measures are prone to recall and desirability bias. The omission of non-users of digital health services can also potentially miss key information about preliminary barriers to adoption.

CONCLUSION

Analysis shows that, despite the progressive uptake of modern health technologies in the Saudi Arabian public sector, the perceived effect of these technologies is heavily and positively correlated with the level to which they were used. The perceptions of healthcare professionals, in particular, administrators, were more positive than those of the general public, who were under significant pressure because of technical issues. The research met the objectives as it was able to measure adoption rates, determine a strong predictive relationship between technology use and perceived outcomes, and reveal key facilitators (including perceived usefulness) and barriers (including system reliability). One of the main scientific contributions of this research is the provision of empirical data from a mixed-methods design, which thus supports the fact that perceived usefulness as a determinant of positive impact is the strongest. The findings present a tested model to understand the integration of technology in the context of the particular socio-cultural context of Saudi Arabia.

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