Analysis of Intention to E-Health Adoption in Nepal

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Abstract

Nepal has used e-heatlh technologies in various forms for more than two decades. While the technologies are intended to be used for easier access to health services, their usage is still quite a minimum. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the factors that affect the adoption of e-health technologies in the healthcare field. The goal of the study is to determine why people's behavioral intentions (BI) to adopt digital health technologies vary. Using quantitative methodology and surveys distributed to a wide variety of stakeholders, including the public, patients, and healthcare professionals, the study identifies key drivers of BI's adoption of e-health. The data highlights the significance of perceived simplicity of usage. When e-health solutions are easy to use, people are more inclined to utilize them (effort expectancy). Furthermore, adoption rates are significantly impacted by facilitating conditions, such as availability of resources and support networks. Additionally, it was shown that two factors were positive predictors of BI for e-health: personal innovativeness in IT, which indicates familiarity with technology, and a strong technology task fit, which matches features to user expectations. It's interesting to note that BI was less affected by social influence and performance expectations. Although legitimate, privacy concerns did not significantly hinder adoption. To overcome acceptance hurdles and realize the transformative potential of e-health solutions, collaboration among stakeholders, including healthcare professionals, technology developers, and end users is essential. Finally, this study offers useful advice on how to enhance acceptance and maximize the revolutionary potential of digital healthcare solutions, in addition to informative data on the factors influencing the uptake of e-health technology.

***Keywords**: Digital Health, User Adoption, Technology Acceptance, Behavior Intention, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Technology Task Fit, Personal Innovativeness in IT, Unified Theory of Acceptance and Use of Technology*

1. Introduction

Fast improvements in technology have resulted in considerable modifications in the healthcare sectors globally in recent decades (Jang et al., 2016). The broad use of ICT has transformed the provision of healthcare, provided excellent services while guaranteed patient efficiency and safety (Blumenthal & Glaser, 2007). Timely, cost-effective, and effective service delivery is deemed critical. According to 2017 research by Hoque et al., e-health—a product of ICT—is essential to the expansion of the health industries in developing nations. As the engine of e-health technology, ICT progress has been acknowledged as a crucial element of the healthcare sector.

The use of ICT to connect healthcare providers, patients, and administrations; to facilitate education for healthcare professionals and users; to encourage innovation in care delivery; and to improve the organization of the health care system is what the World Health Organization (WHO) defines as e-health, according to Blaya et al. (2010). The increasing supply and demand for medical services in both developed and developing countries is commonly perceived as a potential for major improvements in public healthcare sectors, which may be addressed via e-health innovation (Ludwick & Doucette, 2009).

2. Problem Statement

Nestled between China and India, Nepal is a lower-middle-income country with 83% of its people living in rural regions. "Below the poverty line" refers to one-fourth of the population (Siddiquee et al., 2020; Public Health Update, 2019). According to recent statistics from 2021, 94.63% of Nepalese people must walk 60 minutes to reach health care facilities, while 92.54% of them use motorized transportation, taking 15 minutes (Cao et al., 2021). The nation's health infrastructure is also underdeveloped, and its human health index is low and establishing state-of-the-art medical facilities with specialized services in rural locations is a persistent issue (Bhatta, 2013). While it is a factor, Nepal's weak economy is not the only one preventing people from accessing healthcare. Because of Nepal's rough topography, particularly in the highlands, access to health facilities is restricted and transportation and installation are challenging (Shrestha, 2011). The government's aim to provide universal health coverage is not completely explained due to the numerous obstacles that surround the delivery of quality healthcare. Consequently, digital health is seen as one of the most promising tools for ensuring affordable access to healthcare, particularly in difficult-to-reach places (Bradford et al., 2016; Bhatta, 2013). Despite the growing recognition of the potential benefits these technologies offer in terms of improving healthcare accessibility, efficiency, and quality, their integration into the Nepalese healthcare system has been slow and fragmented. This is particularly concerning given the country's diverse geographical landscape, which includes remote and underserved areas where traditional healthcare delivery may be inadequate.

The slow rate of adoption of e-health technologies in Nepal is a notable concern, despite the nation's relatively high digital literacy rate. It's important to recognize that while people may be digitally literate, digital health literacy may not be as prevalent, standing at 31% according to Shrestha (2024).

Additionally, there seems to be a lack of encouragement from various social spheres, including friends, family, society, and national initiatives, which could otherwise incentivize individuals to access digital healthcare services. Implementation challenges further hinder the effective rollout of e-health systems, pointing to the need for cost-effective healthcare solutions that can be readily adopted by the population. Addressing these barriers is crucial for advancing the adoption and integration of e-health technologies into Nepal's healthcare landscape.

3. Research Questions

I. How do perceived benefits, barriers, and facilitating conditions shape e-health adoption intention?

II. What is the role of social influences in influencing the intention to adopt e-health technologies?

III. To what extent do personal innovativeness in IT and privacy concerns impact the intention to adopt e-health technologies in Nepal?

4. Objectives

- To investigate the factors influencing the intention to adopt e-health technologies among individuals in Nepal.
- To examine the role of perceived benefits, barriers, facilitating conditions, and social influences in shaping e-health adoption intention.
- To assess the impact of individual perceptions of ease of use, usefulness, compatibility, personal innovativeness in IT, and privacy concerns on e-health adoption intention.

5. Scope of the Study

1. **Exploration of Constructs**: Examining various factors such as perceived benefits, barriers, facilitating conditions, and social influences on adoption intentions.

2. **Methodology**: Utilizing quantitative methodologies, particularly surveys, to collect data from a diverse demographic, ensuring a comprehensive understanding.
3. **Statistical Analysis**: Employing rigorous statistical analyses to discern significant relationships, patterns, and trends in the collected data.

4. **Limitations Acknowledgement**:

I. **Generalizability**: Findings may not universally apply beyond the sampled population.
II. **Response Biases**: Reliance on self-reported survey data may introduce biases or inaccuracies.
III. **Cross-sectional Design**: Constraints in establishing causal relationships due to the study's snapshot approach.
IV. **Resource and Time Constraints**: Limitations on analysis depth and sample size due to resource and time constraints.
V. **Exclusive Focus on Quantitative Methods**: Potential oversight of qualitative insights that could enrich the findings.

The research was limited to urban areas of Nepal due to time and geographic constraints. However, exploring e-health adoption among digitally literate populations in urban areas provides valuable insights, as digital health literacy may differ from general digital literacy. Focusing on urban regions allowed for efficient data collection and analysis within available resources. Future research should aim to investigate e-health adoption in rural areas to achieve a more comprehensive understanding of adoption trends across diverse settings.

5. **Potential Unexplored Areas**: Acknowledgment that some aspects of e-health adoption in Nepal may remain unexplored or inadequately understood within the study's scope.

6. Literature Review

Studies such as (Pradhan, 2019) have shed light on the benefits and challenges of e-health adoption, particularly in developing countries. For instance, (Subedi & Subedi, 2021) found that e-prescribing among physicians could enhance efficiency and productivity, while (Kc et al., 2019) systematic review highlighted implementation challenges and opportunities in public health hospitals. Similarly, (Morrison et al., 2013) emphasized the potential of e-health technologies like ‘celemedicine’ and improving healthcare access in countries like Nepal.

Sheeran et al. (2015) found that the intention to engage in physical activity was 46% of public health guidelines. This finding indicates that there is a significant gap between the intention to engage in physical activity and actual behavior, highlighting the need to explore strategies to bridge this gap. (Akter & Ray, 2010) conducted a randomized controlled trial and found that mind-body stress reduction interventions were effective and viable in the workplace. This indicates that individuals are motivated to adopt e-health practices for stress reduction and health improvement. However, the specific factors influencing this intention and the extent to which it translates into actual behavior require further investigation.

In e-health adoption, many studies across diverse contexts and countries have delved into the factors influencing the uptake of e- health services (Zhang et al., 2014). These studies have employed various theoretical frameworks, including the TAM, UTAUT, TPB, TRA, and UTAUT-2, to investigate the determinants of adoption behavior. Jung and Loria (2010) explored the TAM model and found that privacy and performance expectancy varied among different adopter groups of mHealth services. Similarly, According to Chiu and Eysenbach (2010) identified variations attitudes towards mHealth adoption based on demographic factors.

According to Phichitchaisopa and Naenna, 2013, “Performance expectancy, effort expectancy, and facilitating conditions emerged as significant factors impacting mHealth adoption”. According to Eisingerich and Bell (2008), “They highlighted the importance of alignment with existing values, needs, and lifestyles of older adults in determining their intention”.

Holden and Karsh (2010) revealed that, "associations between performance expectancy, privacy, social influence, and intention to use mHealth services among older adults". Similarly, privacy, performance expectancy, and trust were identified as influential factors in eHealth adoption among the elderly (Hoque et al., 2017) and convenience and monetary values (Teo and Liu, 2007).

In their study, Hoque and Sorwar (2017) showed "the impact of performance expectancy, effort expectancy, social influence, technological anxiety, and resistance to change on the behavioral intention of elderly individuals". Moreover, PE, EE, SI, FC were found to influence users' adoption in mHealth services (Sun et al., 2013). In developing countries, perceived reliability emerged as a critical factor influencing mHealth adoption intention (Alam et al., 2020). Cost reductions through mobile technology have been observed, although comprehensive long-term evaluations and cost-benefit analyses of mHealth services remain lacking (Gurman et al., 2012).

7. Methodology

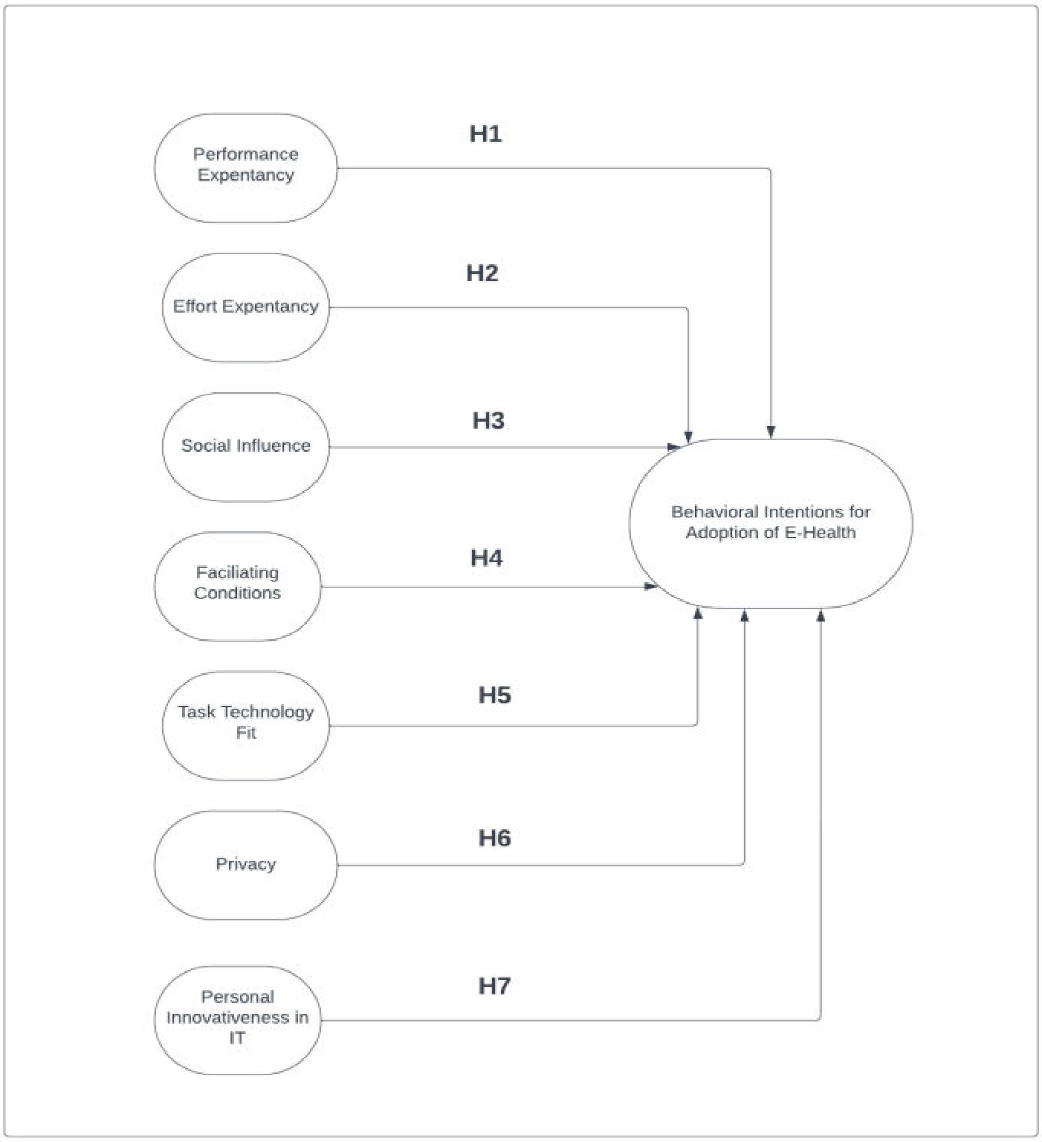

Figure 1: Conceptual Framework

8. Research Design

The research design serves as the blueprint for conducting the study and guides the overall approach to data collection, analysis, and interpretation. In this study on e-health adoption in Nepal, a quantitative research design is employed to systematically investigate the factors influencing individuals' intention to adopt e-health technologies.

Quantitative research is chosen for its ability to generate numerical data that can be analyzed statistically, providing empirical evidence to address the research questions and objectives effectively. This approach allows for the measurement and quantification of variables related to e-health adoption, enabling researchers to identify patterns, trends, and relationships within the data.

The data collection process involved gathering information from various stakeholders involved in healthcare, including healthcare professionals, patients, and caregivers. A comprehensive survey instrument was designed to capture insights into individuals' attitudes and perceptions regarding the adoption of e-health technologies. The survey was administered through online forms. Out of 500 surveys distributed, 385 responses were received for data collection.

The sample for this study was carefully selected to ensure representation from diverse demographics within the healthcare community. Healthcare professionals from different specialties, patients receiving healthcare services, and caregivers providing support to patients were included in the sample. Efforts were made to recruit participants from various healthcare settings, including hospitals, clinics, and community health centers.

A combination of purposive and convenience sampling methods was employed to select participants for the study. Purposive sampling was used to specifically target healthcare professionals with experience in using e-health technologies, as well as patients and caregivers familiar with healthcare services. Convenience sampling was utilized to recruit participants who were readily accessible and willing to participate in the study. The sampling method aimed to ensure a diverse and representative sample that could provide valuable insights into the adoption of e-health technologies across different stakeholder groups in the healthcare sector.

9. Data Analysis

Table 1

Case Summary

	N	%	
Cases	Valid	385	100.0
	Excluded	0	.0
	Total	385	100.0

Table 2

Reliability Test

Construct	Cronbach's Alpha	N of Items
PE	.771	5
EE	.774	5

SI	.797	5
FC	.709	5
TTF	.778	5
P	.786	5
PIIT	.766	5
BI	.721	5

Table 3

Gender

	Frequency	Percent	Valid Percent	Cumulative Percent
Male	189	49.1	49.1	49.1
Female	196	50.9	50.9	100.0
Total	385	100.0	100.0	

Table 4

Age

	1	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 18	3	.8	.8	.8
	18-25	380	98.7	98.7	99.5
	26-40	2	.5	.5	100.0
	Total	385	100.0	100.0	

Descriptive Analysis

Table 5

Descriptive Analysis for Variables

	N Statistic	**Range Statistic**	**Minimum Statistic**	**Maximum Statistic**	**Mean Statistic**	**Std. Error**	**Std. Deviation Statistic**	**Variance Statistic**
PE1	385	3	2	5	3.98	.048	.938	.880
PE2	385	3	2	5	3.90	.043	.850	.723

PE3	385	3	2	5	4.06	.044	.870	.757
PE4	385	3	2	5	3.95	.045	.893	.797
PE5	385	3	2	5	3.98	.044	.869	.755
EE1	385	3	2	5	3.96	.049	.953	.907
EE2	385	3	2	5	3.92	.044	.864	.746
EE3	385	3	2	5	4.04	.044	.862	.743
EE4	385	3	2	5	3.99	.044	.872	.760
EE5	385	3	2	5	4.05	.043	.841	.708
SI1	385	3	2	5	3.96	.047	.915	.837
SI2	385	3	2	5	3.92	.044	.859	.738
SI3	385	3	2	5	3.97	.044	.867	.752
SI4	385	3	2	5	3.96	.044	.859	.738
SI5	385	3	2	5	3.98	.044	.863	.744
FC1	385	3	1	4	2.17	.048	.935	.875
FC2	385	3	1	4	2.15	.042	.826	.682
FC3	385	3	1	4	2.24	.041	.809	.654
FC4	385	3	1	4	2.28	.044	.870	.757
FC5	385	4	1	5	2.36	.049	.952	.907
TTF1	385	3	2	5	4.02	.048	.932	.870
TTF2	385	3	2	5	3.92	.039	.768	.590
TTF3	385	3	2	5	4.03	.042	.827	.684
TTF4	385	3	2	5	4.01	.042	.826	.682
TTF5	385	3	2	5	4.01	.041	.795	.633
P1	385	4	1	5	3.98	.049	.954	.911
P2	385	3	2	5	3.95	.042	.831	.690
P3	385	3	2	5	3.96	.045	.875	.766
P4	385	3	2	5	3.99	.044	.858	.737
P5	385	4	1	5	4.01	.044	.857	.734
PIIT1	385	4	1	5	3.12	.052	1.023	1.046
PIIT2	385	4	1	5	3.10	.047	.918	.843
PIIT3	385	4	1	5	3.19	.047	.913	.833
PIIT4	385	4	1	5	3.23	.049	.960	.922
PIIT5	385	4	1	5	3.29	.053	1.035	1.071
BI1	385	4	1	5	3.15	.053	1.041	1.083

BI2	385	4	1	5	3.17	.049	.963	.927
BI3	385	4	1	5	3.27	.045	.877	.769
BI4	385	4	1	5	3.20	.046	.911	.831
BI5	385	4	1	5	3.15	.046	.898	.807

The provided table offers a comprehensive overview of the descriptive statistics pertaining to different constructs relevant to e-health adoption. Each construct, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Task Technology Fit (TTF), Perceived Risk (P), Personal Innovativeness in IT (PIIT), and Behavioral Intention (BI), is analyzed in terms of its range, minimum, maximum, mean, standard error, standard deviation, and variance. These statistics illuminate the distribution and variability of responses within each construct. Notably, Performance Expectancy and Effort Expectancy exhibit relatively high mean scores, indicating positive perceptions of the benefits and ease of use associated with e-health technologies. Social Influence scores slightly lower, suggesting a moderate impact of social factors on adoption decisions.

In contrast, Facilitating Conditions score lower, indicating perceived inadequacies in supportive conditions for e-health adoption. Task Technology Fit scores relatively high, suggesting a good alignment between technology features and user requirements. Personal Innovativeness in IT and Behavioral Intention also garner positive mean scores, indicating an inclination towards innovation and an intention to adopt e-health technologies among respondents.

These insights offer valuable guidance for policymakers and health practitioners seeking to enhance e-health adoption within the healthcare system, emphasizing areas of strength and potential improvement.

Table 6

Co-relation Analysis

		PE	EE	SI	FC	TTF	P	PIIT	BI
PE	Pearson Correlation	1	.429**	.463**	-.110*	.367**	.339**	-.111*	.088
	Sig. (2-tailed)		<.001	<.001	.032	<.001	<.001	.030	.086
	N	385	385	385	385	385	385	385	385
EE	Pearson Correlation	.429**	1	.517**	-.012	.417**	.324**	-.007	.146**
	Sig. (2-tailed)	<.001		<.001	.814	<.001	<.001	.891	.004
	N	385	385	385	385	385	385	385	385
SI	Pearson Correlation	.463**	.517**	1	-.138**	.459**	.374**	-.130*	.086
	Sig. (2-tailed)	<.001	<.001		.007	<.001	<.001	.011	.093
	N	385	385	385	385	385	385	385	385
FC	Pearson Correlation	-.110*	-.012	-.138**	1	-.033	-.073	.973**	.302**
	Sig. (2-tailed)	.032	.814	.007		.514	.154	<.001	<.001
	N	385	385	385	385	385	385	385	385

TTF	Pearson Correlation	.367**	.417**	.459**	-.033	1	.403**	-.018	.107*
	Sig. (2-tailed)	<.001	<.001	<.001	.514		<.001	.724	.036
	N	385	385	385	385	385	385	385	385
P	Pearson Correlation	.339**	.324**	.374**	-.073	.403**	1	-.055	.073
	Sig. (2-tailed)	<.001	<.001	<.001	.154	<.001		.282	.151
	N	385	385	385	385	385	385	385	385
PIIT	Pearson Correlation	-.111*	-.007	-.130*	.973**	-.018	-.055	1	.294**
	Sig. (2-tailed)	.030	.891	.011	<.001	.724	.282		<.001
	N	385	385	385	385	385	385	385	385
BI	Pearson Correlation	.088	.146**	.086	.302**	.107*	.073	.294**	1
	Sig. (2-tailed)	.086	.004	.093	<.001	.036	.151	<.001	
	N	385	385	385	385	385	385	385	385

****. 0.01 level (2-tailed).**
***. 0.05 level (2-tailed).**

Table 7
Regression Analysis

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.348a	.121	.105	.55777
a. Predictors: (Constant), PIIT, EE, P, PE, TFT, SI, FC				

The model has a moderate explanatory power, as indicated by an R Square of .121, suggesting that approximately 12.1% of the variance in the dependent variable (BI - Behavioral Intention) is explained by the independent variables (PIIT, EE, P, PE, TFT, SI, FC).
The adjusted R Square, which adjusts for the number of predictors in the model, is .105, indicating that the model's explanatory power slightly decreases when considering the number of predictors.

Table 8
Anova table

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.205	7	2.315	7.441	<.001b
	Residual	117.286	377	.311		

Total	133.490	384

a. Dependent Variable: BI

b. Predictors: (Constant), PIIT, EE, P, PE, TFT, SI, FC

The ANOVA table shows that the regression model is statistically significant (F = 7.441, p < .001), indicating that the model significantly predicts the variance in the dependent variable (BI).

Table 9

Coefficient Table

Coefficientsa

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error			
1	(Constant)	2.489	.300		8.293	<.001
	EE	.082	.055	.088	1.474	.141
	PE	.042	.053	.045	.785	.433
	SI	.034	.057	.037	.590	.556
	FC	.339	.208	.344	1.628	.104
	TFT	.037	.057	.038	.656	.512
	P	.022	.051	.024	.428	.669
	PIIT	-.024	.179	-.029	-.136	.892

a. Dependent Variable: BI

Among the predictors, only Facilitating Condition (FC) has a statistically significant coefficient (B = 0.339, p = .104). However, this p-value is marginally above the conventional threshold of .05, suggesting a potential trend toward significance.

Other predictors such as EE, PE, SI, TFT, P, and PIIT do not have statistically significant coefficients, as their p-values are greater than .05.

The model suggests that while there is a relationship between the predictors (PIIT, EE, P, PE, TFT, SI, FC) and the dependent variable (BI), only the Facilitating Condition (FC) has a potentially meaningful influence on behavioral intention towards e-health adoption.

However, it's important to note that the overall explanatory power of the model is moderate, indicating that there may be other factors not accounted for in the model that influence behavioral intention towards e-health adoption in Nepal.

Future research may explore additional variables or refine the measurement of existing constructs to improve the predictive power of the model.

10. Findings

Effort expectancy, facilitating conditions, and personal innovativeness in IT significantly influence e-health adoption intention in Nepal. Correlation and regression analyses confirm the positive relationship between these factors and behavior intention, supporting the research hypothesis. Factors such as performance expectancy, social influence, Technology Task Fit, and privacy concerns show weak or non-significant relationships with adoption intention. Efforts to enhance user experience, provide support infrastructure, and foster innovation are crucial for increasing adoption rates. Significant predictors align with the research questions and objectives, offering insights for policymakers, healthcare providers, and technology developers. Simplifying user interfaces, providing clear instructions, and offering technical assistance could enhance adoption rates. Targeting innovative early adopters can drive broader acceptance and adoption of e-health initiatives in Nepal. Traditional social norms and privacy concerns may not be significant barriers to e-health adoption. Tailored strategies emphasizing simplicity, convenience, access to support, and data security are essential for promoting e-health adoption in Nepal.

11. Conclusion

Effort expectancy, facilitating conditions, and personal innovativeness in IT significantly influence e-health adoption intention in Nepal. Factors such as performance expectancy, social influence, Technology Task Fit, and privacy concerns show weak or non-significant relationships with adoption intention. Efforts to enhance user experience, provide support infrastructure, and foster innovation are crucial for increasing adoption rates. Significant predictors align with the research questions and objectives, offering insights for policymakers, healthcare providers, and technology developers. Simplifying user interfaces, providing clear instructions, and offering technical assistance could enhance adoption rates. Targeting innovative early adopters can drive broader acceptance and adoption of e-health initiatives in Nepal. Traditional social norms and privacy concerns may not be significant barriers to e-health adoption.

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