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Factors Influencing the Adoption of Online Insurance Services Offered through Digital Wallet Platforms in Kathmandu, Nepal

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Abstract

Despite the explosive growth of digital wallet applications in Nepal, the insurance services offered by these applications have not yet been widely adopted by the country's population. For this study, data from a survey of 169 consumers in Kathmandu, Nepal, were analyzed using the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and four additional constructs related to insurance and digital wallets. Partial Least Squares (PLS) and Structural Equation Modeling (SEM) were used to identify the factors influencing the behavioral intention of young consumers in urban areas of Nepal to purchase insurance services via digital wallet platforms. Results from the PLS-SEM model after 5000 bootstrap samples to enhance reliability indicate that three of the eight hypothesized factors were statistically significant and contributed to the Behavioral Intention to Adopt. The significant constructs included Service Efficiency and Customer Experience, Personal Capability and Social Influence, and Institutional and Policy Support. Additionally, the eight constructs accounted for 45.7% of the explained variance in the outcome variable, Behavioral Intention to Adopt. Furthermore, only 5.3% of those surveyed purchased insurance through a digital wallet application, while 48.5% were unaware of the insurance services offered by digital wallet platforms. The findings suggest that the factors leading to the greatest increase in the intention of young consumers to use digital wallets for insurance purchases are improvements in the quality of the services provided by the digital wallets, improvements in the communication of the policies that regulate those digital wallets, and increased awareness of the insurance services that are offered by the platforms.

Keywords

Digital Wallet, Online Insurance, InsurTech, TAM, UTAUT, PLS-SEM, Nepal, Technology Adoption, Technology Acceptance Model, Theory of Acceptance and Use of Technology, Partial Least Squares-Structural Equation Modeling

1. Introduction

1.1. Background and Context

The financial services sector is constantly changing, especially with the rise of mobile connectivity. This constant change affects FinTech or financial technology companies, such as firms offering digital wallets, especially across multiple Asian countries. These digital wallets have evolved into platforms that enable individuals to access services beyond payments, including insurance purchases (Karki et al., 2024; Wei et al., 2025). Nepal, for example, has seen a rapid growth in mobile payment platforms since 2009, with the launch of eSewa by F1 Soft International. According to the Nepal Rastra Bank, the number of mobile payment users in Nepal has skyrocketed since the COVID-19 pandemic (Nepal Rastra Bank, 2024). Nonetheless, the insurance industry in Nepal has not kept up with the growth of the financial services sector. The insurance penetration rate in Nepal remains among the lowest in Asia, with most insurance sales through agents, who are inaccessible to the country's young population, who favor digital platforms. Thus, the growth of digital wallets presents an unexplored opportunity for the insurance industry in Nepal. Academic literature in studying the adoption of digital insurance typically uses the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Pahuja & Chitkara, 2016; Ismail & Sum, 2025; Wei et al., 2025). Available literature within the country, however, has examined only the adoption of online banking (Subedi & Tamang, 2023) and mobile payment platforms (Karki et al., 2024). Thus, this investigation intends to fill a research gap in the insurance industry regarding the use of digital wallets.

1.2. Problem Statement

Even with Nepal's current digital wallet infrastructure, insurance purchases through these wallets remain negligible. Our survey of 169 Nepali respondents showed that 91.1% use at least one digital wallet, while 33.7% currently hold some form of insurance, whether life or non-life. However, only 5.3% of the population has purchased insurance policies through digital wallets. In fact, 48.5% of respondents were unaware that insurance services existed within these digital wallets. The most cited reasons for not adopting insurance policies in digital wallets include a lack of awareness of the services offered (48.5%), distrust of digital applications (36.9%), and fraud concerns (28.1%). However, as of this writing, no study has examined the factors that inhibit Nepalis from adopting insurance policies through digital wallets.

1.3. Research Questions

This study is guided by the following two research questions: What factors influence the adoption of online insurance services offered through digital wallet platforms by young urban consumers in Kathmandu, Nepal? How do these factors relate to the behavioral intention of these consumers to adopt such insurance services?

1.4. Research Objectives

This study has the following research objectives: identify the factors influencing the young consumers in Kathmandu in adopting insurance applications using their digital wallets; examine the relationships among these factors using Partial Least Squares with Structural Equations Modeling (PLS-SEM), and provide recommendations to digital wallet companies, insurance providers, and the Nepali government based on the study's findings.

1.5. Scope and Importance of the Study

The data collection will be limited to the Kathmandu Valley, which includes the cities of Kathmandu, Lalitpur, and Bhaktapur, as well as Nepal's financial and digital services hub. The target population for this study will be young adults aged 18 to 35 with prior experience using digital financial services. Four different institutions will be surveyed to reach the intended population: Shankardev Campus, CAN Consultancy, Model Institute of Technology (MIT) Nepal, and Tribhuvan University Institute of Engineering, Thapathali Campus. The variable to be measured is Behavioral Intention to Adopt these digital financial services, as measured in the TAM and UTAUT models.

Because the adoption rate of these digital services is negligible across Nepal, it is currently unlikely that the population will adopt them anytime soon. To help accelerate digital insurance adoption, this study delivers the first investigation into individuals' technology adoption intentions in Nepal, using a model extended with constructs related to insurance and the characteristics of a developing economy. Practically, the study delivers recommendations for digital wallet companies on the type of platform and services that should be developed to encourage insurance adoption, for insurance companies on methods of distributing their insurance digitally, and for the regulators of those companies on the types of regulations that will best facilitate the development of the insurance market in the nation.

2. Literature Review

2.1. Digital Financial Services and FinTech Adoption

FinTech is the application of digital technologies to the delivery of financial services, with digital wallets being among the FinTech innovations of recent times (Karki et al., 2024). Studies in various countries, including Malaysia, India, Ghana, Tanzania, and Nepal, found that factors influencing the adoption of digital wallets include perceived usefulness, ease of use, social influence, and security. In Nepal, Karki et al. (2024) applied the Innovation Resistance Theory to the TAM while investigating 417 digital wallet users in Kathmandu. The study revealed that factors that substantially affected the adoption of digital wallets included their usability, the value they offered users, and the image they projected relative to other digital wallets. Factors related to risk, traditional attitudes towards technology, and the cost of using these applications were not found to be significant. Furthermore, eSewa was found to be the most widely adopted digital wallet application in Nepal (53% of all users), a finding further substantiated by the present study. Subedi and Tamang (2023) applied TAM to investigate the factors influencing the adoption of online banking services in Nepal. Their findings indicated that the perceived usefulness of online banking applications was positively associated with adoption of the service ($\beta = 0.140$, $p < 0.05$), as was the ease of use of the banking applications ($\beta = 0.457$, $p < 0.05$). However, factors such as Nepalese customers' trust in their banks and the level of support the Nepalese government provides to those banks were not significantly related to the adoption of online banking services.

2.2. Insurance Technology (InsurTech) and Online Insurance

InsurTech is the application of digital innovation to the insurance industry (Wei et al., 2025). The embedding of insurance into digital wallet applications in emerging economies has significantly facilitated the expansion of the insurance industry. Pahuja and Chitkara (2016) identified the major factors influencing the adoption of e-insurance applications in India as sustainability, cost-effectiveness, and operational benefits, as well as customer-related issues. Ismail and Sum (2025) found that the factor most strongly influencing Malaysian youth to adopt online insurance applications was the perceived usefulness of these applications, followed by users' subjective norms. Finally, Wei et al. (2025) found that the technology acceptance model in the insurance industry was successfully applied to the adoption of digital health insurance in China. Both urban and rural Chinese residents showed significant relationships between performance expectancy, effort expectancy, and social influence when adopting digital health insurance applications. Additionally, these individuals' financial literacy substantially affected the relationship between performance expectancy and insurance adoption.

2.3. Conceptual Models: TAM and UTAUT

Davis's (1989) TAM claims that behavioral intention to adopt or use a specific technology is based on two beliefs: that the technology will be perceived as *useful* for performing a task, and that it will be *easy to use* for that task. The TAM approach has been widely validated and has since been expanded, for example into TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), to account for additional constructs and variables that may influence individuals' intentions to adopt technology, with particular applications in digital finance (Chong et al., 2010; Subedi & Tamang, 2023). One of the most well-known extensions of TAM is the UTAUT, proposed by Venkatesh et al. (2003), which incorporates five additional theories, resulting in four main constructs inside the model. These constructs include *performance* expectancy, which relates to the belief that using a system will improve performance; *effort* expectancy, which relates to the belief that using the system will require minimal effort; *social influence*, which reflects the influence that others in a society have upon an individual's decision to adopt a technology, especially in societies like Nepal that are collectivist in their social structure; and *facilitating conditions*, which relates to the idea that certain technological environments or conditions will allow for the use of the technology, similar to the Digital Ecosystem Readiness construct in this research study.

2.4. Extended Constructs and Conceptual Framework

Building on the TAM and UTAUT models, we incorporate several additional constructs. The construct of *security and regulatory assurance* concerns the trustworthiness of information shared by insurance companies and oversight bodies, such as Nepal Rastra Bank and Beema Samiti (Pahuja & Chitkara, 2016). *Personal capability and social influence* would be the operationalized variable that considers individuals' overall level of digital literacy, their experience with e-government services, and the societal influence of endorsements from their social circles and family (Venkatesh et al., 2003; Ismail & Sum, 2025). *Economic and marketing factors* consider the impact of factors such as the cost and value of insurance products and the incentives that encourage their purchase (Karki et al., 2024; Pahuja & Chitkara, 2016). The constructs of *service efficiency and customer experience* encompass the speed with which the insurance company processes claims and provides services, the variety of insurance products available for different durations, and the quality of customer service provided (Wei et al., 2025). Finally, the last construct of interest is *institutional and policy support*, which encompasses the government's interest in the development and regulation of digital financial services (Chong et al., 2010; Subedi & Tamang, 2023). The dependent variable of interest is the Behavioral Intention (INT) to adopt mobile health insurance applications. Eight independent variables are considered to have an impact on the dependent variable of interest: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Security and Regulatory Assurance (SEC), Personal Capability and Social Influence (PCSI), Economic and Marketing Factors (ECO), Service Efficiency and Customer Experience (SER), Digital Ecosystem Readiness (DIG), and Institutional and Policy Support (INS). The model used in this study draws on constructs and models from Subedi and Tamang (2023), Karki et al. (2024), Ismail and Sum (2025), Pahuja and Chitkara (2016), Wei et al. (2025), and Vanitha (2023).

2.5. Mathematical Representation of the Conceptual Framework

The proposed framework can be expressed as a latent-variable adoption model in which the Behavioral Intention (INT) to adopt online insurance through digital wallet platforms is modeled as a function of eight theoretically derived predictors

(PU, PEOU, SEC, PCSI, ECO, SER, DIG, and INS). More specifically, the model can be represented as:

$$INT_i = \beta_0 + \beta_1 PU_i + \beta_2 PEOU_i + \beta_3 SEC_i + \beta_4 PCSI_i + \beta_5 ECO_i + \beta_6 SER_i + \beta_7 DIG_i + \beta_8 INS_i + \zeta_i$$

2.6. Research Hypotheses

In this study, we propose eight directional hypotheses:

H1: Perceived Usefulness (PU) positively influences Behavioral Intention to Adopt (INT).

H2: Perceived Ease of Use (PEOU) positively influences Behavioral Intention to Adopt (INT).

H3: Security and Regulatory Assurance (SEC) positively influences Behavioral Intention to Adopt (INT).

H4: Personal Capability and Social Influence (PCSI) positively affect Behavioral Intention to Adopt (INT).

H5: Economic and Marketing Factors (ECO) positively influence Behavioral Intention to Adopt (INT).

H6: Service Efficiency and Customer Experience (SER) positively influence Behavioral Intention to Adopt (INT).

H7: Digital Ecosystem Readiness (DIG) positively influences Behavioral Intention to Adopt (INT).

H8: Institutional and Policy Support (INS) positively influences Behavioral Intention to Adopt (INT).

3. Research Methodology

3.1. Research Design

A quantitative cross-sectional survey research design was adopted to test the study's hypotheses (Creswell & Creswell, 2018). This design allows for both descriptive and analytical interpretations of the collected data. The study framework's use of multiple theories reflects the consensus in the literature that no one theory can comprehensively explain the acceptance of digital financial services in developing countries (Chong et al., 2010; Karki et al., 2024).

3.2. Population, Sampling, and Data Collection

The target population is young urban consumers aged 18 to 35 residing or studying in the Kathmandu Valley, and who have some prior exposure to digital financial services. This group was targeted specifically because it represents the primary users of digital wallets in Nepal (Nepal Rastra Bank, 2024). A convenience sampling strategy, with some purposive selection of sites for survey distribution, was used. The survey locations included the CAN Consultancy firm and three educational institutions: the Shankardev Campus, the Model Institute of Technology (MIT) Nepal, and the Tribhuvan University Institute of Engineering, Thapathali

Campus. The surveys were distributed using Google Forms and on paper at different locations. Google Forms were emailed, and QR codes for the survey were placed in high-traffic areas within these institutions. At each site, recruitment was on an intercept basis: the researcher was present in person and invited any willing individual who happened to be on site to take part, rather than drawing on a predetermined list of participants. Because the researcher was physically present throughout data collection, repeat participation could be monitored directly. In addition, the Google Forms instrument was configured to record each respondent's email address and to restrict submissions to one response per account. The responses were subsequently screened so that no email address or respondent name appeared more than once across the paper and online submissions. A response was treated as valid only when the participant consented to take part, satisfied the screening criteria (aged 18 to 35, residing or studying in the Kathmandu Valley, and having prior experience with digital financial services), and completed the survey items required for the analysis; incomplete, duplicate, or ineligible submissions were removed prior to analysis. Data were collected over two weeks, yielding a total of 169 valid responses. Although the initial target sample size was 900, the number of responses collected (N = 169) exceeds the minimum required for PLS-SEM analysis (Hair et al., 2022). Additionally, the number of responses collected satisfies Green's (1991) recommendation for the number of cases required to perform multivariate regression analyses. It should nonetheless be acknowledged that, because the sample is a convenience sample drawn largely from university settings, it is dominated by students aged 18 to 24. The findings should therefore be generalized only to similar young, urban, digitally active users, rather than to the wider Nepali population.

3.3. Survey Instrument

A well-structured questionnaire in English and Nepali was developed to measure perceptions of the nine constructs, using 54 items, rated on a five-point Likert scale from 5 (Strongly Agree) to 1 (Strongly Disagree). Most of the items were derived from established scales used in the literature related to information systems, technology adoption, and insurance. Items related to the concepts of Risk and Transaction Cost were worded negatively to allow reverse coding. The nine constructs measured were the Perceived Usefulness of the services (4 items), Perceived Ease of Use (5 items), Security and Regulatory Assurance (7 items), Personal Capability and Social Influence (10 items), Economic and Marketing Factors (7 items), Service Efficiency and Customer Experience (7 items), Digital Ecosystem Readiness (6 items), Institutional and Policy Support (4 items), and Behavioral Intention to Adopt (4 items).

3.4. Analytical Schema

The analyses performed in this research study included data cleaning, calculation of composite scores, descriptive statistics, and correlational analyses. The main analysis, however, was Partial Least Squares Structural Equation Modeling (PLS-SEM), with 5000 bootstrap resamples to estimate path coefficients. PLS-SEM was used in preference to covariance-based SEM methods due to the study's exploratory nature, sample size, data distribution, and the multidimensionality of some constructs (Hair et al., 2022). Consistent with the two-step approach recommended by Anderson and Gerbing (1988), the PLS-SEM analysis performed both a measurement model analysis and a structural model analysis.. The model assesses the validity and dependability of the research survey items. Data reliability was assessed using Cronbach's Alpha and composite reliability. Values of at least 0.70 are considered statistically reliable (Nunnally & Bernstein, 1994). Convergent validity was assessed with the Average Variance Extracted analysis, with values of at least 0.50 indicating convergent validity (Fornell & Larcker, 1981). Discriminant validity was assessed with the Heterotrait-Monotrait Ratio, with ratios of 1.00 or less indicating discriminant validity (Henseler et al., 2015). For reflective indicators, the measurement relationship can be written as

$$x_{ij} = \lambda_{ij}\eta_j + \varepsilon_{ij}$$

where x_{ij} is an observed survey item i for latent construct j; λ_{ij} is the indicator loading; η_j is the latent construct; and ε_{ij} is the measurement error term. This formulation assumes that each observed item is a manifestation of the underlying latent variable it is intended to measure.

Reliability and convergent validity were evaluated using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted. Cronbach's Alpha was calculated conceptually as

$$\alpha_j = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_T^2}\right)$$

where k is the number of items in the construct j, σ_i^2 is the variance of each item, and σ_T^2 is the variance of the total construct score. Composite Reliability was specified as

$$CR_j = \frac{\left(\sum_{i=1}^{k}\lambda_{ij}\right)^2}{\left(\sum_{i=1}^{k}\lambda_{ij}\right)^2 + \sum_{i=1}^{k}Var\left(\varepsilon_{ij}\right)}$$

and Average Variance Extracted was specified as

$$AVE_j = \frac{\sum_{i=1}^{k}\lambda_{ij}^2}{k}$$

These indicators are used to assess the internal consistency of the constructs and to evaluate each construct's explanation of the variance in its indicators. Discriminant validity is assessed through the Heterotrait-Monotrait ratio.

Beyond PLS-SEM, several other analyses can be conducted to gain further insight into the model. Such analyses include examining variance inflation factors to assess multicollinearity; utilizing F-squared analyses to determine the effect size of the constructs; using CAP Q-squared analyses to assess the model's predictive relevance; and analyzing actual insurance adoption based on wallet insurance using logistic regression. Each of these analyses can be performed because the current study includes both intention and adoption analyses, particularly given the finding that only 5.3% of the population has adopted wallet-based insurance. A subset of these analyses was carried out to assess the model's robustness. An ordinary least squares model was constructed using the same variables as both a linear model and a natural log transformation. Additionally, the structural model was re-fitted as a covariance-based model under three specifications, and the variance inflation factors for all models were calculated. These analyses were performed as a form of cross-validation for the study; the structural equation model results are the study's main results. Additional models were constructed to determine whether the same significant predictors appeared across the alternative models. The variance inflation factors for the models indicated no multicollinearity among the eight predictors of insurance adoption. Furthermore, each supplementary model identified the same three significant paths as the main PLS-SEM model.

4. Findings

4.1. Respondent Demographics

Most of the respondents were aged 18 - 24 years, as they were all university students (Table 1). Most of the samples were from Kathmandu (76.9%), followed by Lalitpur (11.8%) and Bhaktapur (11.2%). The sample was slightly male-dominant (53.3%). Most of the respondents had a bachelor's degree or higher (61.5%), while 38.5% had completed their +2 (high) school. Figure 1 illustrates the marked gap between the use of digital wallets (91.1%) and both having insurance coverage (33.7%) and purchasing insurance from their digital wallet (5.3%). The drop from the middle to the last bar in Figure 1 represents the problem this study addresses.

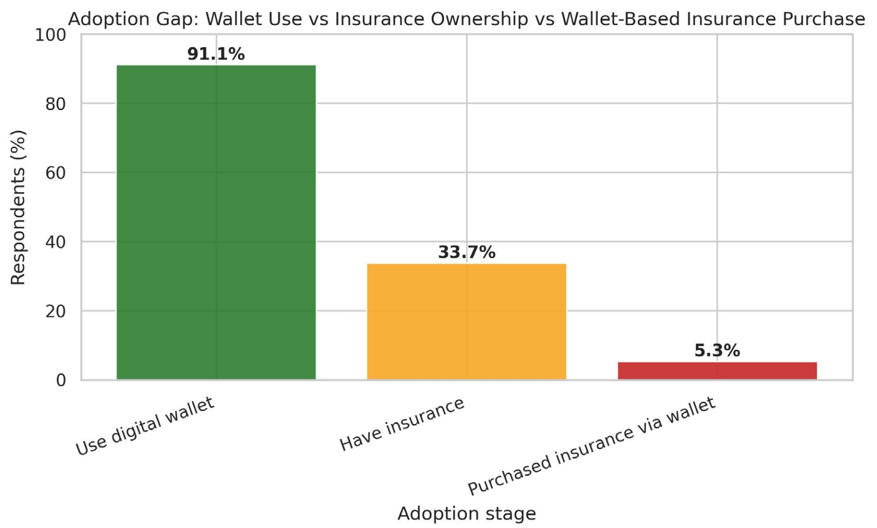

Figure 1. Adoption gap: Wallet, insurance ownership, and wallet-based insurance purchase.

Table 1. Profile of respondent demographics (N = 169).

Variable	Category	Frequency	%
Age	18 - 24 years	125	74.0%
	25 - 29 years	37	21.9%
	30 - 35 years & others	7	4.1%
Gender	Male	90	53.3%
	Female	77	45.6%
	Other/Prefer not to say	2	1.1%
Education	Bachelor's degree	85	50.3%
	+2/High school	65	38.5%
	Master's or above & others	19	11.2%
Occupation	Student	121	71.6%
	Employed (full-time)	33	19.5%
	Others (part-time, self-employed)	15	8.9%
Uses Digital Wallet	Yes	154	91.1%
	No	15	8.9%
Has Insurance	Yes	57	33.7%
	No	112	66.3%
Aware of Insurance via Wallet	Yes	87	51.5%
	No	82	48.5%
Purchased Insurance via Wallet	Yes	9	5.3%
	No	160	94.7%

4.2. Descriptive Statistics

All constructs' means scored above the midpoint of the measurement scale (Table 2). The high mean value for Institutional and Policy Support ($\bar{x}$ = 3.642) indicates that respondents have a strong orientation towards regulatory engagement. Many respondents also recognized the usefulness of digital services in general (Perceived Usefulness: $\bar{x}$ = 3.700), despite the low use of digital insurance services. The lowest mean value was observed for the Behavioral Intention to Adopt construct ($\bar{x}$ = 3.092), indicating that although most respondents intend to use digital insurance services, they have not yet committed to using such technologies. The Security and Regulatory Assurance construct received a relatively low score from users of insurance companies' digital services ($\bar{x}$ = 3.020), indicating worries about data privacy and regulatory compliance. Figure 2 and Figure 3 display the data graphically. Figure 2 depicts the comparison of the mean scores of each construct relative to one another. The constructs having the highest mean scores are placed towards the top of the graph, while those with the lowest mean scores are depicted towards the bottom of the graph. Figure 3 depicts the histogram of the mean scores of each construct. The histogram is roughly symmetrical around a point just above the midpoint of the scale, consistent with the skewness coefficients for each construct in Table 2.

Table 2. Descriptive statistics of construct composite scores (N = 169).

Construct	N	Mean	SD	Min	Max	Skew	Kurt
Perceived Usefulness (PU)	169	3.700	0.750	1.00	5.00	−0.999	1.814
Perceived Ease of Use (PEOU)	169	3.514	0.786	1.00	5.00	−0.972	1.206
Security & Regulatory Assurance (SEC)	169	3.020	0.509	1.57	4.57	−0.183	0.484
Personal Capability & Social Influence (PCSI)	169	3.443	0.707	1.00	5.00	−0.861	1.539
Economic & Marketing Factors (ECO)	169	3.184	0.478	1.57	4.29	−0.739	0.884
Service Efficiency & Customer Experience (SER)	169	3.399	0.846	1.00	5.00	−0.778	0.564
Digital Ecosystem Readiness (DIG)	169	3.464	0.844	1.00	5.00	−0.854	0.748
Institutional & Policy Support (INS)	169	3.642	0.916	1.00	5.00	−0.818	0.791
Behavioral Intention to Adopt (INT)	169	3.092	0.797	1.00	5.00	−0.284	0.437

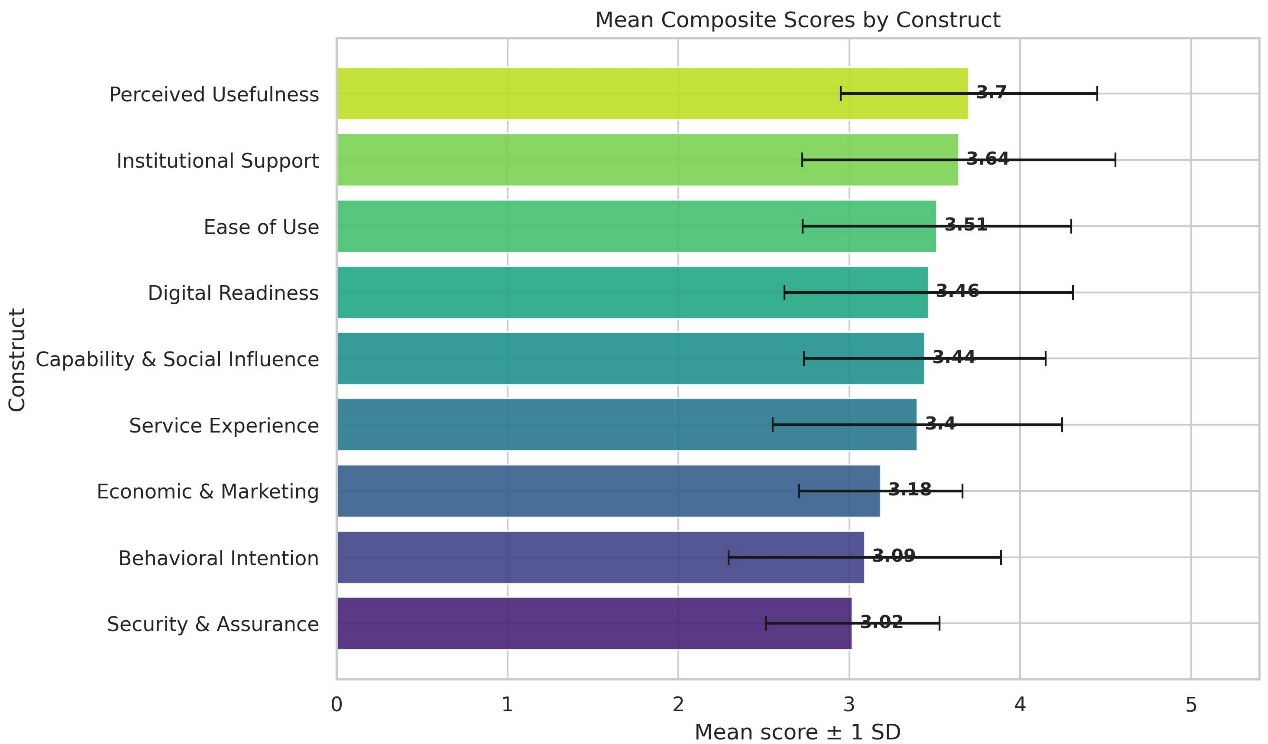

Figure 2. Mean composite scores by construct (Ordered high to low, ±1 SD). Notes: Error bars denote ±1 standard deviation. N = 169.

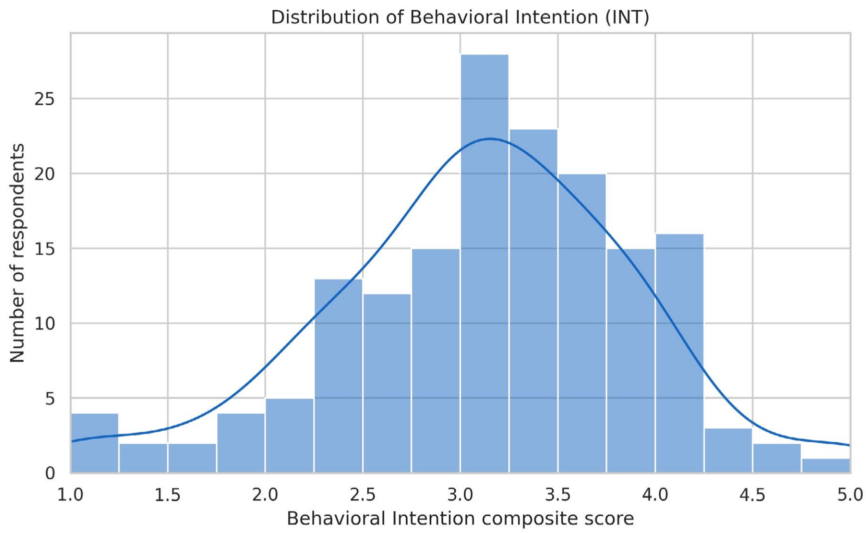

Figure 3. Distribution of behavioral intention to adopt (INT). Notes: Composite behavioral intention to adopt score (1 - 5). N = 169.

All eight independent constructs showed significant positive correlations with Behavioral Intention to Adopt (INT). The constructs that exhibited the highest correlations with Behavioral Intention to Adopt were Service Efficiency and Customer Experience (r = 0.595), followed by Personal Capability and Social Influence (r = 0.500), Institutional and Policy Support (r = 0.492), and Economic and Marketing Factors (r = 0.490), as seen in **Table 3**. Furthermore, none of the correlations between the constructs exceeded the multicollinearity threshold of r = 0.85; the highest correlation was between PCSI and DIG (r = 0.621). Thus, these bivariate analyses support each of the eight hypothesized relationships between the constructs and the concept of Behavioral Intention to Adopt. **Figure 4** presents the same analysis as a heatmap, revealing the direction of correlations among the constructs and indicating that none of the correlations approach the multicollinearity threshold of r = 0.85.

Table 3. Pearson correlation matrix (N = 169).

Construct	PU	PEOU	SEC	PCSI	ECO	SER	DIG	INS	INT
PU	1.000*								
PEOU	0.637*	1.000*							
SEC	0.385*	0.453*	1.000*						
PCSI	0.585*	0.645*	0.510*	1.000*					
ECO	0.440*	0.498*	0.347*	0.570*	1.000*				
SER	0.428*	0.500*	0.471*	0.530*	0.535*	1.000*			
DIG	0.479*	0.550*	0.429*	0.621*	0.567*	0.577*	1.000*		
INS	0.409*	0.483*	0.352*	0.401*	0.458*	0.521*	0.497*	1.000*	
INT	0.338*	0.377*	0.389*	0.500*	0.490*	0.595*	0.409*	0.492*	1.000*

Notes: * implies $p < 0.001$ (two-tailed). Lower triangle shown. All correlations are statistically significant.

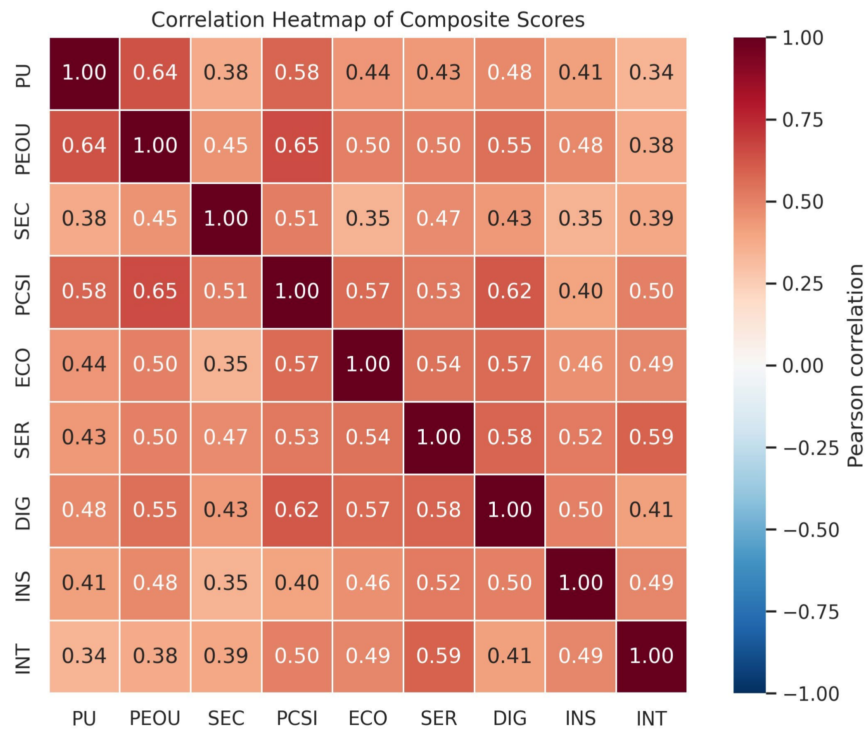

Figure 4. Correlation heatmap of construct composite scores. Notes: Pearson correlations among the nine composite scores. N = 169.

4.3. Correlation Analysis

See Table 3 and Figure 4.

4.4. Measurement Model Assessment

As shown in Table 4, seven of the nine constructs showed acceptable to excellent reliability, with coefficients ranging from 0.821 to 0.888. The constructs of Security and Regulatory Assurance and Economic and Marketing Factors demonstrated reliability coefficients below the accepted threshold for internal consistency due to their multidimensional nature (Peterson, 1994). However, both constructs were above the Composite Reliability threshold (CR = 0.715), the preferred measure of reliability for PLS-SEM models (Hair et al., 2022). The three constructs of Security and Regulatory Assurance (SEC), Personal Capability and Social Influence (PCSI), and Economic and Marketing Factors (ECO) had AVE values below the recommended threshold of 0.50. However, each of these constructs had a CR value above 0.70 and was supported by theoretical literature. The HTMT for each construct was below the discriminant validity threshold of 0.85 (the highest value was 0.82 for the PCSI and DIG constructs).

Table 4. Reliability and convergent validity.

Construct	N	Cronbach's α	CR	AVE	α Status	AVE Status
Perceived Usefulness (PU)	4	0.835	0.890	0.670	✓ Adequate	✓ Adequate

Continued

Perceived Ease of Use (PEOU)	5	0.835	0.886	0.608	✓ Adequate	✓ Adequate
Security & Regulatory Assurance (SEC)	7	0.457	0.715	0.311	⚠ Below 0.70	⚠ Below 0.50
Personal Capability & Social Influence (PCSI)	10	0.863	0.891	0.450	✓ Adequate	⚠ Below 0.50
Economic & Marketing Factors (ECO)	7	0.355	0.715	0.374	⚠ Below 0.70	⚠ Below 0.50
Service Efficiency & Cust. Experience (SER)	7	0.888	0.913	0.600	✓ Adequate	✓ Adequate
Digital Ecosystem Readiness (DIG)	6	0.845	0.888	0.572	✓ Adequate	✓ Adequate
Institutional & Policy Support (INS)	4	0.821	0.887	0.664	✓ Adequate	✓ Adequate
Behavioral Intention to Adopt (INT)	4	0.852	0.901	0.695	✓ Adequate	✓ Adequate

Notes: Thresholds: $\alpha \geq 0.70$; CR ≥ 0.70; AVE ≥ 0.50 (Fornell & Larcker, 1981; Hair et al., 2022). ✓ = meets threshold; ⚠ = below threshold.

4.5. Structural Model: Hypothesis Testing

The model's R^2 indicated that it explained 45.7% of the variance in users' Behavioral Intention ($R^2 = 0.457$, Adj. $R^2 = 0.430$). This is a large effect size according to Cohen's (1988) benchmarks. Three of the hypotheses were supported by the study findings. Hypothesis 6, which posited a relationship between SER and INT ($\beta = 0.337$, $p < 0.001$), was supported. Additionally, Hypothesis 4 (PCSI → INT, $\beta = 0.279$, $p = 0.012$) and Hypothesis 8 (INS → INT, $\beta = 0.198$, $p = 0.016$) were also found to be statistically significant and thus supported. Five of the hypotheses (H1, H2, H3, H5, and H7) were not supported. However, each of these five variables exhibited a significant bivariate correlation with users' intention (**Table 3**). The negative coefficients for PU, PEOU, and DIG reflect suppression effects rather than problematic collinearity; the variance inflation factors reported in **Table 5** remain below the levels of concern, while these constructs remain positively correlated with intention in the bivariate analyses and share variance with other adoption-related predictors in the model (Cohen et al., 2003).

Table 5. Variance inflation factors for the eight predictors.

Predictor	VIF	Tolerance	Interpretation
Personal Capability & Social Influence (PCSI)	2.479	0.403	No concern
Perceived Ease of Use (PEOU)	2.295	0.436	No concern
Digital Ecosystem Readiness (DIG)	2.114	0.473	No concern
Service Efficiency & Cust. Experience (SER)	1.939	0.516	No concern
Perceived Usefulness (PU)	1.882	0.531	No concern
Economic & Marketing Factors (ECO)	1.825	0.548	No concern
Institutional & Policy Support (INS)	1.615	0.619	No concern
Security & Regulatory Assurance (SEC)	1.500	0.667	No concern

Notes: VIF < 3 = no concern; 3 - 5 moderate; 5 - 10 high; >10 serious. Tolerance = 1/VIF. N = 169.

Supplementary Regression, Multicollinearity, and Covariance-Based SEM

We wanted to confirm that the SEM results were not an artifact of the PLS-SEM algorithm's instability. Hence, least-squares regression and covariance-based path analysis were performed on the nine composite variables, and the predictor variables were screened for multicollinearity. Each of these three analyses revealed the same results, which are presented in Tables 5-7 and Figure 5. The multicollinearity analysis was performed first. Table 5 shows that each variance inflation factor is below 2.5, which is well below the cautionary value of 5 and the problematic value of 10. The two highest variance inflation factors are for the variables of Personal Capability and Social Influence (VIF = 2.479) and for Perceived Ease of Use (VIF = 2.295). Furthermore, each tolerance statistic is above 0.40. Thus, each of the predictors correlates with the others (as indicated in Table 3), but not to such an extent as to create problems for the model. Consequently, while the negative multivariate coefficients for PU, PEOU, and DIG were surprising, they do not necessarily indicate a problem with the data that was used to estimate the model structure.

Table 6. Comparison of five multivariate regression models forecasting behavioral intention to adopt.

Predictor (→ INT)	Model 1: Full Linear	Model 2: Reduced Linear	Model 3: Final Linear	Model 4: Full Log	Model 5: Reduced Log
Perceived Usefulness (PU)	−0.031 (0.699)			−0.039 (0.643)	
Perceived Ease of Use (PEOU)	−0.096 (0.279)			−0.173 (0.080)	−0.189 (0.033)
Security & Regulatory Assurance (SEC)	0.064 (0.374)			0.097 (0.171)	
Personal Capability & Social Influence (PCSI)	0.247 (0.008)	0.175 (0.022)	0.220 (0.002)	0.233 (0.016)	0.216 (0.019)
Economic & Marketing Factors (ECO)	0.156 (0.050)	0.122 (0.114)		0.183 (0.026)	0.161 (0.047)
Service Efficiency & Customer Experience (SER)	0.358 (<0.001)	0.338 (<0.001)	0.368 (<0.001)	0.368 (<0.001)	0.354 (<0.001)
Digital Ecosystem Readiness (DIG)	−0.111 (0.190)			−0.131 (0.152)	
Institutional & Policy Support (INS)	0.227 (0.003)	0.190 (0.008)	0.212 (0.003)	0.242 (0.002)	0.218 (0.005)
Adjusted R2	0.430	0.428	0.423	0.420	0.416
Akaike Info Criterion (AIC)	394.49	391.14	391.71	397.31	395.62
Bayes Info Criterion (BIC)	422.66	406.79	404.23	425.48	414.40
Hannan-Quinn	405.93	397.49	396.79	408.74	403.24

Notes: Cell entries are standardized β with *p*-values within parentheses; predictor removed at the $p \leq 0.10$ screening step. Models 4 and 5 use natural-log-transformed predictors. N = 169.

Table 7. Covariance-based SEM: Fit of three structural configurations.

Configuration	R2 (INT)	CFI	TLI	RMSEA	SRMR
Config 1, Full direct (saturated)	0.457	1.000			0.000
Config 2, Reduced direct	0.442	0.999	0.992	0.030	0.016
Config 3, Mediated (DIG → PCSI → INT)	0.442	0.942	0.781	0.190	0.083

Note: Config 1 is saturated (df = 0), so TLI and RMSEA are undefined. N = 169.

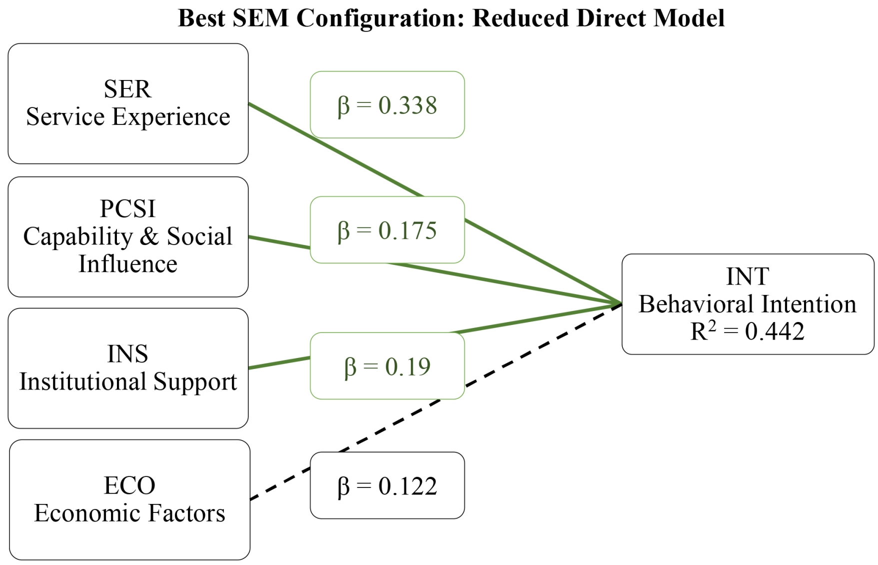

Figure 5. Best-fitting covariance-based SEM configuration (Reduced direct model). Notes: Solid lines indicate significance at $p < 0.05$; the dashed line (ECO → INT) indicates no significance. Standardized β is shown on each path. Model fit: CFI = 0.999, TLI = 0.992, RMSEA = 0.030, SRMR = 0.016.

Table 6 presents the regression models estimating the impact of the eight predictors on the variable of interest, Behavioral Intention to Adopt. Five different models are estimated: the linear model that includes all eight predictor variables (Model 1); a reduced linear model that includes only those variables significant at $p \leq 0.10$ (Model 2); a final linear model that retains only the variables remaining significant after the reduced model (Model 3); and the natural-log analogs of the full and reduced models (Models 4 and 5). The linear model that includes all eight predictors (Model 1) explains 43.0% of the adjusted variance in the outcome variable, which is essentially identical to the adjusted R^2 of 0.430 for the PLS-SEM model. Both the reduced model (Model 2) and the final model (Model 3) improve on the full model across the information criteria. Model 3, which drops Economic and Marketing Factors after it became insignificant in Model 2 ($p = 0.114$), records the lowest Bayesian Information Criterion (BIC = 404.23) and Hannan-Quinn value (HQ = 396.79) of all five models and is effectively tied with Model 2 on the Akaike Information Criterion (AIC = 391.71 versus 391.14). Because every retained predictor in Model 3 is statistically significant, and it is the most parsimonious specification, it was adopted as the final linear model. The explained variance is essentially identical across these models, with adjusted R^2 values of 0.428 for Model 2 and 0.423 for Model 3. Neither of the natural-log models was preferred to the linear models. Within each of the five models, the variables that had the strongest relationship with the Behavioral Intention to Adopt outcome were found to be the variables of Service Efficiency and Customer Experience, followed by Institutional and Policy Support and Personal Capability and Social Influence; the same three variables that were significant within the PLS-SEM model.

Finally, the structural model was re-fitted as a covariance-based path model under three different configurations (Table 7). Configuration 1 included direct paths from each of the eight predictors to the Behavioral Intention construct. Because the model was saturated (df = 0), its fit indices were not interpretable. However, they were reported for completeness. Configuration 2 included only the direct paths from the four strongest predictors to Behavioral Intention. This model showed an excellent fit (CFI = 0.999, TLI = 0.992, RMSEA = 0.030, SRMR = 0.016) and explained 44.2% of the variance in Behavioral Intention. Configuration 3 included the direct paths from the four strongest predictors to the intention construct, as well as a mediated route in which Digital Ecosystem Readiness influenced Behavioral Intention through the mediating effects of both the Personal Capability and Social Influence constructs. Although the path from Digital Ecosystem Readiness to each of the two mediators was statistically significant (β = 0.621, $p < 0.001$), the model fitted with the mediated effect was poor (RMSEA = 0.190, SRMR = 0.083); thus, this model was set aside in favor of the model with only the direct effects. Figure 5 depicts the covariance-based model that best fits the data. Moreover, regardless of the method used to estimate the structural model's parameters, the same factors emerged as the most consequential for users' intentions to adopt digital insurance: service experience, institutional support, and personal and social capability. Thus, economic components were found to have a positive effect on Behavioral Intention (though not a statistically significant effect) (β = 0.122, $p = 0.114$).

4.6. Estimated Structural Equation

Based on the standardized PLS-SEM path coefficients, the estimated Behavioral Intention to Adopt is

$$\begin{aligned} INT_i = &-0.033PU_i - 0.097PEOU_i + 0.100SEC_i + 0.279PCSI_i \\ &+ 0.260ECO_i + 0.337SER_i - 0.105DIG_i + 0.198INS_i + \zeta_i \end{aligned}$$

If we retained only the three statistically significant paths, for a more parsimonious model re-estimated on those three predictors alone, Behavioral Intention to Adopt is estimated as:

$$INT_i = 0.220PCSI_i + 0.368SER_i + 0.212INS_i + \zeta_i$$

The coefficients reported in this reduced equation were obtained by re-estimating the model on the three statistically significant predictors, rather than by reusing the full-model estimates reported in Table 8. For this reason, they differ slightly from the corresponding full-model coefficients; the standardized coefficient for Service Efficiency and Customer Experience, for instance, rises from 0.337 to 0.368, while those for Personal Capability and Social Influence and Institutional and Policy Support adjust to 0.220 and 0.212, respectively. This reduced specification explains a comparable share of the variance in Behavioral Intention to Adopt ($R^2 = 0.433$).

Table 8. Structural model results and hypothesis testing.

H	Path (→ INT)	β	T-Stat	*p*-Value	95% CI Low	95% CI High	Decision
H1	PU → INT	−0.033	−0.362	0.717	−0.212	0.148	Not Supported
H2	PEOU → INT	−0.097	−1.200	0.230	−0.258	0.062	Not Supported
H3	SEC → INT	0.100	0.897	0.370	−0.122	0.320	Not Supported
H4	PCSI → INT	0.279	2.513	0.012*	0.063	0.499	Supported
H5	ECO → INT	0.260	1.541	0.123	−0.072	0.591	Not Supported
H6	SER → INT	0.337	4.121	<0.001***	0.176	0.500	Supported
H7	DIG → INT	−0.105	−1.361	0.173	−0.256	0.045	Not Supported
H8	INS → INT	0.198	2.403	0.016*	0.038	0.360	Supported

Notes: Bootstrap samples = 5000. Two-tailed test. * $p < 0.05$; *** $p < 0.001$. $R^2 = 0.457$; Adjusted $R^2 = 0.430$.

The model with the reduced specification is that of the best-fitting models identified in the robustness analysis, which includes the linear regression model and the direct SEM model, but is limited to the three levers for adoption intention: the experience with the insurance service provider, the personal and social capability to adopt the insurance service, and the institutional support for such adoption. Service Efficiency and Customer Experience had the largest positive effect on Behavioral Intention to Adopt, followed by Personal Capability and Social Influence, and then by Institutional and Policy Support. Each of these three constructs was the only variable with a statistically significant effect on the intention to adopt the wallet-based insurance service. Security and Regulatory Assurance and Economic and Marketing Factors had positive coefficients but were not statistically significant. Finally, the negative coefficients for Perceived Usefulness, Perceived Ease of Use, and Digital Ecosystem Readiness do not indicate a negative relationship between these constructs and Behavioral Intention to Adopt; they are positively correlated with the behavioral outcome in bivariate analyses. The negative coefficients indicate suppression effects in the model, as these constructs are correlated with other adoption-related constructs. Overall, the equation indicates that intention to adopt the wallet-based insurance service among young consumers with urban residences was driven primarily by experience with the insurance provider, capability to use the provider's services, and the availability of institutional support for such adoption.

5. Discussion

5.1. Service Efficiency and Customer Experience (SER): The Dominant Driver (H6)

The most critical finding is that SER is the strongest predictor (β = 0.337, $p < 0.001$) of Behavioral Intention to Adopt insurance technology solutions, a finding that carries considerable theoretical and practical weight. As discussed, insurance products are of the type that require payment of premiums in advance, with benefits realized only upon submission of a claim. Therefore, the efficiency and experience of the claims submission and management process are critical factors in the decision to adopt insurance technology. Furthermore, because individuals cannot evaluate the quality of insurance technology solutions before purchasing such insurance products, their beliefs about the efficiency of insurance technology providers at the time of claims will form the basis of their decisions to adopt those providers. This finding is consistent with Karki et al. (2024), who found that factors influencing the adoption of insurance technology in Nepal include those related to insurance users' experience with the features of the insurance provider's technology ($\beta = 0.271$, $p < 0.001$). Furthermore, Wei et al. (2025) reported that the effort expectancy of users of digital insurance platforms in China was significant among both urban ($\beta = 0.239$) and rural ($\beta = 0.209$) populations. Thus, both groups of authors support the conclusion that the effort and time required of insurance customers to use and submit claims to insurance technology providers is the single most important factor in individuals' intention to adopt those platforms.

5.2. Personal Capability and Social Influence (PCSI): The Social Architecture of Adoption (H4)

The second most significant predictor in this study was PCSI ($\beta = 0.279$, $p = 0.012$). This demonstrates that those with higher levels of digital literacy and experience using various digital services in their daily lives are significantly more likely to intend to use digital insurance services. Nepal is a country famous for its close-knit and collectivist culture. That is, close family members and peers all play a significant role in an individual's financial decisions. This factor is reflected in the UTAUT model's focus on social influence (Venkatesh et al., 2003). Ismail and Sum (2025) found that this factor was a significant predictor of online insurance adoption among Malaysian youth, with $\beta = 0.353$. Furthermore, similar findings were reported by Karki et al. (2024) in their study of digital payment technologies in Nepal. Strategies that target individuals' social lives and encourage them to use these platforms alongside their peers are among the lower-cost approaches to promoting adoption of these technologies.

5.3. Institutional and Policy Support (INS): The Regulatory Trust Anchor (H8)

The finding that INS is significantly related to the intention to adopt ($\beta = 0.198$, $p = 0.016$) is the most important in this study. Given the nature of insurance products, customers often feel uncertain about whether their policies will deliver the promised value. Through government licensing and strict regulations governing insurance products, consumers face lower risk when using insurance products from banks such as the Nepal Rastra Bank and the Beema Samiti. This variable is significant within the scope of this InsurTech study, even though the government support was not significant in Subedi and Tamang's (2023) study on the impact of government support on online banking adoption. Insurance products carry more risk than banking transactions; hence, the importance of government regulation in the insurance industry. Relatedly, customers in other developing economies have demonstrated that government support affects their intention to adopt online banking and insurance technologies. For instance, Chong et al. (2010) demonstrated that government support for the development of online banking strongly influenced customers' intention to adopt these technologies.

5.4. Nonsignificant Predictors: Interpretive Considerations

Perceived Usefulness (H1), Perceived Ease of Use (H2), Security and Regulatory Assurance (H3), Economic and Marketing Factors (H5), and Digital Ecosystem Readiness (H7) were all statistically insignificant. However, each of these variables showed significant correlations with INT. However, the multivariate analysis showed that their insignificance is attributable to their relationships with the three significantly predictive variables (SER, PCSI, and INS). More specifically, the insignificance of the PU variable may indicate that the insurance feature within the digital wallet is in its initial stages of development in Nepal. While individuals are aware of the usefulness of the digital wallet, they have not yet developed a perception of the usefulness of the insurance within the wallet. PEOU was not significant due to the high rate of existing digital wallet users (91.1% of the sample population); ease of use is assumed to be an attribute of the wallet. Finally, the reliability of the SEC variable was low ($\alpha = 0.457$), indicating that this concept comprises multiple dimensions that should be measured separately in future studies. The ECO construct was nearly significant ($p = 0.123$) yet exhibited a meaningful beta of 0.260 and a low internal consistency ($\alpha = 0.355$). Finally, the DIG and PCSI variables are correlated ($r = 0.621$); the negative beta for DIG reflects this high correlation with PCSI.

5.5. The Awareness Gap: A Pre-Adoption Structural Barrier

Beyond the structural model is the significant impact of the awareness gap. Specifically, 48.5% of individuals were unaware of wallet-based insurance before completing this study's survey. Additionally, 47.5% of those who do not intend to adopt wallet insurance cite a lack of awareness of these products as their leading barrier to adoption. This barrier to adoption is another precondition that must be eliminated before improvements to the structural model increase adoption of wallet insurance. Therefore, efforts to increase awareness of wallet insurance, such as supply-side awareness initiatives, wallet insurance application notifications, in-application insurance feature discovery campaigns, and in-application insurance marketing campaigns, are just as necessary as improvements to the product and service elements of wallet insurance.

Beyond the structural model and the technology acceptance model elements, another model for analyzing wallet insurance adoption is the consumer utility model. Consumer adoption of insurance products can be viewed as a financial decision. Consumers must decide whether the perceived utility of the wallet insurance product exceeds the perceived risks of using it. This decision can be represented as a net adoption utility function:

$$\begin{aligned} U_i = {} & \theta_1 Benefit_i + \theta_2 Convenience_i + \theta_3 SocialApproval_i \\ & + \theta_4 InstitutionalTrust_i - \theta_5 PerceivedRisk_i - \theta_6 Cost_i \end{aligned}$$

where U_i is the net utility that the respondent i associates with adopting wallet-based insurance. Adoption becomes more likely when net utility is positive:

$$Pr\left(Adopt_i = 1\right) = Pr\left(U_i > 0\right)$$

or, in logistic form

$$Pr\left(Adopt_i = 1\right) = \frac{1}{1 + e^{-U_i}}$$

which explains why the concepts of perceived usefulness and ease of use, in general, were not the dominant themes in the study. For transactions with a digital wallet, convenience and ease of use are often sufficient. With insurance, however, consumers must also believe that the policy will be honored, that claims will be processed, that institutions will protect them, and that the policy provides value.

5.6. Theoretical Contributions

This study makes four main theoretical contributions to academic literature. First, it develops and tests a model that integrates TAM and UTAUT, along with constructs derived from the study's context, in a previously underexplored field: the adoption of wallet-embedded insurance in Nepal. While many studies have examined the use of digital wallets, online banking, and even insurance products, this study investigated their use alongside insurance in the context of a developing economy.

Second, the study found that constructs related to service quality and social influence could have a major impact on consumers' decisions to adopt wallet-embedded insurance, much like the Perceived Usefulness and Perceived Ease of Use constructs in TAM have traditionally influenced insurance adoption. This finding suggests that, rather than considering only the usefulness and ease of use of wallet insurance as previously recommended, those who wish to adopt these insurance products should also take into account factors such as the quality of the insurance provider and the influence of others in the consumer's social circle.

Third, this study confirms that the construct of Institutional and Policy Support is a major factor that influences the adoption of wallet-embedded insurance products. In Nepal and other developing economies, consumers consider the regulatory and institutional context of the insurance provider as one of the factors that affect their decision to adopt the insurance products offered by these digital wallets.

Fourth, the study's analyses indicate that the process by which consumers adopt insurance products may be distinct from that modeled in the TAM framework.

The gap between the use of digital wallets, ownership of insurance policies, awareness of wallet-embedded insurance, and the actual purchase of these products suggests that consumers must first become aware of these products before any of the constructs of the TAM model can influence their decision to adopt them. Thus, this finding further contributes to the InsurTech literature and can inform future studies on this topic.

6. Conclusion and Future Research

This study aimed to investigate the factors influencing the intention of young people in Kathmandu to adopt insurance services via digital wallet platforms. Based on the framework of TAM-UTAUT and the survey of 169 young people in Kathmandu, three out of eight hypotheses were substantiated: the hypotheses of service efficiency and customer experience (H6, $\beta = 0.337$, $p < 0.001$), personal capability and social influence (H4, $\beta = 0.279$, $p = 0.012$) and institutional and policy support for digital wallet platforms (H8, $\beta = 0.198$, $p = 0.016$). The model accounted for 45.7% of the variance in young people's intention to adopt insurance services through digital wallets (a large effect). Despite the high proportion of the younger generation in Kathmandu who use digital wallet platforms (91.1%), the proportion of those who use insurance services through these platforms is negligible (5.3%). Additionally, half of the young individuals surveyed in Kathmandu were unaware that their digital wallet platforms offered insurance services (48.5%). The most frequently cited reasons for the lack of adoption of insurance services within these digital wallets were a lack of awareness of their existence within the digital wallets (47.5%), distrust of the digital services (36.9%), and fear of the misuse of their personal data within these platforms (28.1%).

6.1. Implications for Practice

6.1.1. Digital Wallet Operators

The insurance feature should be made prominent within the mobile applications of eSewa, Khalti, and IME Pay. The insurance purchase experience should be simplified through user-friendly language and features, and by providing in-app customer support to address insurance-related questions and issues. Additionally, the existing structure of the organizations' referral programs can be leveraged to encourage the social sharing of insurance policies as identified in this study.

6.1.2. Insurance Companies and InsurTech Providers

Any insurance company entering the digital wallet space should offer microinsurance products with low premiums and quick insurance claim settlement procedures that can be relayed within the digital wallet application. The messaging for the insurance product should focus on the claims process rather than its features. Insurance companies can also benefit from co-branding their insurance products with the various digital wallets, especially in countries where digital wallets like eSewa have high penetration rates.

6.1.3. Regulators and Policy Makers

The Nepal Rastra Bank and the Beema Samiti may require digital wallet applications to display information on the licensing of insurance products. Publishing claims-settlement standards for these digital insurance policies will help address worries about distrust and fraud in insurance companies, which are the second- and third-most common reasons for non-adoption of these products. Conducting nationwide awareness and informational campaigns about the benefits of these insurance products may help narrow the difference between their intended and actual adoption.

6.2. Recommendations for Future Research

Having established the baseline of current research on digital insurance adoption in Nepal and provided suggestions for future research, future studies should use larger, more balanced samples with respect to demographic characteristics and include participants of all age groups from across the nation. Furthermore, future research would benefit from employing longitudinal studies to examine how the determinants of adoption may change once the digital insurance market matures in Nepal, or to model the relationship between intention to purchase digital insurance policies and individuals' actual purchase behavior. Additionally, each construct should be further broken down into its constituent components to improve their discriminant validity in the model, particularly for the current study's SEC and ECO constructs. With the projected growth in the number of Nepalese individuals who adopt digital insurance providers and companies, it will be of interest to examine these actual behaviors as the new dependent variable, replacing the intention variable. Other areas of interest for future research studies include conducting interviews with individuals who use these digital insurance providers to determine the reasons for their adoption. Finally, it will also be of interest to incorporate cross-country comparisons between Nepal and countries such as India and Bangladesh, as well as other countries in the South Asian region. Following the example of Wei et al. (2025), who found that the construct of financial literacy was a significant moderator of the relationship between the performance of a technology-related expectancy and the adoption of that technology in the context of digital insurance in China, it will also be of interest to investigate whether the construct of financial literacy is similarly important in the context of digital insurance adoption in Nepal.

6.3. Concluding Remarks

Digital insurance in Nepal stands at an important point in its development. The infrastructure for digital wallet-based insurance has already been established. Wallet applications such as eSewa, Khalti, and IME Pay are already very popular among young consumers for financial transactions. However, insurance penetration in the country is relatively low. Additionally, as consumers age, insurance products such as health, life, accident, travel, and asset protection insurance become more relevant to their financial lives. Despite these factors, the digital insurance and digital wallet infrastructure for Nepal remains largely unexplored. Only 5.3% of the population has purchased insurance through a digital wallet. Expanding the adoption of digital wallet insurance requires making the service visible, understandable, credible, trustworthy, and reliable. Service efficiency and customer experience are the strongest predictors of the intention to use digital insurance services. For this reason, the adoption process for digital insurance through digital wallets in Nepal can be divided into three stages: awareness of the service, intention to use it, and actual adoption. Awareness of the service is necessary to initiate the process of forming an intention to use digital insurance applications. The intention to use a product is created through the quality of the service, the influence of others, the individual's capabilities, and the visibility of institutional support. Finally, the actual adoption of a digital wallet insurance service occurs only when the consumer perceives that the benefits of using the service outweigh the risks. Therefore, digital wallets should focus on making insurance services visible and easy to use. Insurance companies should focus on developing simple insurance products for mobile applications and reliable claims processes. Finally, the regulators should focus on making consumer protection and insurance oversight for digital wallets visible to consumers when they purchase insurance products through digital wallets. Overall, each of these stakeholders in Nepal's digital insurance ecosystem can play an important role in transforming a rarely used digital wallet insurance feature into an essential element of financial inclusion for the country's growing population.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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