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Factors Affecting Adoption of Fintech in Nepal

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ABSTRACT

Purpose – The study aims to explore the factors affecting adoption of fintech in Nepal and measures relationship and impact among those factors.

Design/methodology/approach – The study adopted descriptive and casual comparative research design and convenient sampling techniques. A sample size of 352 respondents while 70 questionnaires were used for the study. Hence, the study makes use of ordinary least square regression to test the hypotheses formulated for the adoption of fintech in Nepal.

Findings – The study finds that perceived usefulness (PU) is the most significant factor driving fintech adoption, with a strong positive correlation and a highly significant relationship in the OLS regression analysis. Additionally, perceived ease of use (PEU), perceived awareness (PA), perceived risk (PR), perceived cost (PC), and trust in technology (TT) all have significant positive relationships with fintech adoption, though their influence is generally weaker than that of PU.

Research limitations – The study's limitations include a small, non-representative sample and the potential for bias in survey responses, as well as the inability to establish cause and effect due to its cross-sectional nature.

Practical implications – Fintech companies in Nepal should focus on making their services more useful, easy to use, and trustworthy by designing user-friendly products, ensuring transparency, and maintaining strong security. Additionally, they should offer competitive pricing and clear communication to address cost concerns and build trust among users.

Originality/value – This study is a novel contribution in studying factor affecting adoption of fintech in Nepal by examining the dependent and independent variables; i.e., Perceived Awareness, Perceived Usefulness, Perceived Risk, Perceived Ease of Use, Perceived Cost and Trust in Technology.

Keywords: Adoption of Fintech, Perceived Awareness, Perceived Usefulness, Perceived Risk, Perceived Ease of Use, Perceived Cost and Trust in Technology.

Introduction

According to Fama (1970), the Efficient Market Hypothesis (EMH) states that financial markets quickly digest all available information; thus, consistently earning excess returns is improbable. On the other hand, recent technologies within FinTech—including algorithmic trading and blockchain—have bolstered market efficiency by enhancing transparency and information symmetry (Philippon, 2016). Blockchain and DeFi as emerging FinTech innovations help to redesign corporate good governance, offering a solution to the agency problem in a system that is transparent and decentralized (Beck et al., 2022). These technologies can mitigate the classical separation of ownership and control described by creating novel mechanisms to align stakeholder incentives and increase accountability (Jensen & Meckling,1976).

This change began with the emergence of electronic banking in the 1970s to form the basis for the sophisticated network of digital payments, lending platforms, and blockchain-based solutions we know today (Gomber et al., 2018). Although there is no generally agreed-upon definition of FinTech, the concept broadly describes the creative implementation of technology to improve financial services and disrupt traditional forms of financial intermediation (Thakor, 2020). Fintech, an interdisciplinary area combining insights from finance, technology, and business innovation, is revolutionizing the way consumers transact with one another and businesses (Leong & Sung, 2018), as illustrated, for example, with payment solutions such as mobile applications. Digital transformation is no longer an option, and every industry is forced to adopt innovations that will create more value in its operations and bring a competitive advantage to the organization (Martinčević et al., 2020). In finance, this evolution led to FinTech—the convergence of finance and technology—empowering businesses and consumers to make the best of their financial transactions through digitized applications.

In the context of Nepal, narrowed to the realm of global financial services, the term FinTech denotes the blending of technology and finance risks to create fast, efficient, and accessible services to users across the world (Khatiwada et al., 2019). The emergence of the digital world is not only being felt by existing economies but also in emerging markets where new solutions are filling the void left by outdated forms of finance. As the technology landscape continues to evolve, FinTech's role in shaping inclusive, efficient financial ecosystems becomes ever more vital across diverse economies. The quality of digital banking services significantly influences customer satisfaction and loyalty, with user-friendly interfaces and robust security measures being particularly crucial for building trust (Gautam et al., 2023). As financial institutions enhance their online platforms, these improvements not only strengthen customer relationships but also contribute to broader economic growth and stability.

Statement of the Problem

Despite the assertion by Fama (1970) that markets efficiently incorporate all available information, rendering sustained excess returns unlikely, the rapid adoption of FinTech innovations—such as algorithmic trading and blockchain—has introduced new dynamics that may further enhance market efficiency by improving transparency and reducing information asymmetry (Philippon, 2016). This raises the question of whether these technological advancements have empirically strengthened market efficiency or created new arbitrage opportunities that challenge traditional EMH assumptions. Recent studies indicate that FinTech adoption, particularly algorithmic trading and blockchain, has significantly improved market efficiency by reducing latency, enhancing price discovery, and minimizing information asymmetry (Biais et al., 2015; Cong & He, 2019). However, some evidence suggests that these technologies may also introduce short-term inefficiencies due to high-frequency trading strategies and fragmented liquidity, complicating the EMH's applicability in modern markets (Budish et al., 2015). Though, the potential benefits of mobile payment services, privacy concerns and security limitations continue to hinder widespread adoption. Addressing these concerns, along with emphasizing convenience and usefulness, is crucial for fostering increased adoption, which can be facilitated through stronger regulatory policies and enhanced security measures (Kim et al., 2016). Understanding user intention toward fintech adoption remains a challenge due to the varying influence of perceived benefits and risks across different adopter groups. The differential impact—particularly the dominant role of legal risk and convenience—highlights the need for a nuanced approach that considers the adoption stage and specific motivational or deterrent factors influencing user behavior (Hyun, 2018). The adoption of fintech services among women remains comparatively low due to persistent barriers related to trust, usability, awareness, and financial knowledge. This gap underscores the need for gender-sensitive strategies that address these specific determinants to promote inclusive fintech engagement and support equitable financial empowerment (Batola, 2019). The gap between consumer expectations and firm offerings continues to hinder broader adoption. To bridge this gap, firms must better understand and align both internal capabilities and external consumer factors, facilitating more effective communication and ensuring successful fintech integration (Utami et al., 2021). Perceived ease of use, innovation, trust, and government support significantly and positively influence the adoption of fintech services, as they enhance user engagement by improving functionality, fostering reliability, encouraging novelty, and reinforcing institutional legitimacy (Akhtar et al., 2022). These factors collectively shape users' behavioral intentions toward fintech adoption within the framework of the Technology Acceptance Model. Although fintech adoption is increasing globally, there remains a lack of consensus on the most comprehensive set of factors influencing user behavior. Existing models like TAM and UTAUT provide useful foundations, but recent findings indicate that variables such as trust, financial literacy, and safety, along with an integrated multi-theoretical framework, are essential to fully understand and explain fintech adoption dynamics (Firmansyah et al., 2022). Customer adoption of fintech services is increasingly shaped by perceptions of data security, usability, and usefulness, yet gaps remain in fully understanding how these factors collectively influence trust and the perceived value of promotional efforts. Addressing these gaps is essential for fintech providers seeking to build customer confidence and improve adoption strategies in a highly competitive digital financial environment (Zhang, 2023).

In Context of Nepal Perceived usefulness, ease of use, and peer influence drive FinTech adoption, while security concerns, self-efficacy, and generational disparities act as key barriers (Rakhi et al., 2017; Mathur et al., 2018). Improved service quality—particularly in security, privacy, and interface design—significantly enhances user satisfaction and loyalty, suggesting institutional interventions can accelerate adoption (Gautam et al., 2023). While digital wallets are recognized as a key driver of financial inclusion in Nepal, the specific factors influencing their adoption—such as perceived usefulness, price value, and trust—remain insufficiently understood (Shrestha & Tamang, 2023). Furthermore, the extent to which adoption directly enhances financial inclusion requires empirical validation to guide policymakers and financial service providers. Effort expectancy, trust, and perceived usefulness exhibit a direct and significant influence on FinTech adoption intentions in urban Nepal (Parajuli et al., 2024). Security, privacy, and social factors indirectly affect adoption through perceived usefulness, while effort expectancy partially mediates adoption, and trust operates solely as a direct determinant.

The major objectives of the study are to determine the factors affecting adoption of FinTech in Nepal, to examine the impacts, and to identify the relation between various independent variables like perceived usefulness, perceived ease of use, perceived risk, perceived awareness, perceived cost and trust on technology.

Literature Review

The adoption and awareness of FinTech are influenced by a multidimensional set of factors, including individual perceptions, technological features, and institutional environments (Utami et al., 2021). Empirical studies demonstrate that perceived usefulness, ease of use, and financial literacy significantly drive adoption intentions, particularly in developing economies (Guo & Peng, 2024), while trust and security concerns remain critical barriers (Firmansyah et al., 2022). Research in Laos reveals a stark gap between awareness (31%) and actual usage (4%), highlighting systemic adoption challenges despite relatively high financial literacy (Morgan & Trinh, 2019). Educational attainment and employment status positively correlate with FinTech engagement, whereas older populations exhibit lower adoption rates, suggesting demographic disparities in technology uptake (Morgan & Trinh, 2019; Firmansyah et al., 2022). These findings underscore the need for integrated interventions addressing both user-level behavioral factors and structural barriers like digital infrastructure and regulatory frameworks (Utami et al., 2021).

The literature highlights multiple factors influencing the perceived usefulness and adoption of FinTech, with studies emphasizing both drivers and barriers to adoption. Kajol et al. (2022) identify key motivators such as perceived usefulness, ease of use, compatibility, trust, and security, alongside inhibiting factors, underscoring the role of technological and behavioral determinants in digital financial transactions. Singh et al. (2020) further reveal that while perceived usefulness and social influence shape usage intentions, actual adoption is primarily driven by ease of use and social influence, with older users prioritizing security concerns. Batola (2019) emphasizes the importance of gender-inclusive strategies in FinTech adoption, suggesting that financial organizations must address disparities to enhance financial inclusion. Utami et al. (2021) consolidate these findings, demonstrating that FinTech adoption is shaped by a combination of consumer and firm-level factors, with effective communication being critical to aligning strategies with user needs. Collectively, these studies underscore the need for a multifaceted approach that integrates technological accessibility, trust-building measures, and targeted outreach to diverse demographic groups to optimize FinTech adoption.

The literature consistently identifies perceived ease of use as a critical determinant of FinTech adoption across diverse contexts. Hornuf et al. (2024) demonstrate that in Sub-Saharan Africa, both perceived ease of use and perceived usefulness emerge as primary adoption drivers, while highlighting a research gap regarding supply-side influences from FinTech providers. Complementing these findings, Nangin et al. (2020) establish that perceived ease of use significantly enhances customer trust in FinTech services, though surprisingly find security concerns to be statistically insignificant in their study. Further supporting this paradigm, Natsir et al. (2023) reveal that perceived ease-of-use positively influences user attitudes toward FinTech adoption, alongside perceived usefulness and risk perceptions. Bhaskaran (2021) extends this understanding by linking ease of use to specific financial behaviors, particularly in crowdfunding contexts, while emphasizing the moderating role of risk assessment.

The literature presents nuanced findings regarding the role of perceived risk in FinTech adoption, with studies revealing both inhibitory and facilitative effects across different contexts. Purwantini & Anisa (2021) demonstrate an unexpected positive relationship between perceived risk and adoption intention among micro-enterprises, suggesting that certain users may interpret risk signals as indicators of innovation potential, particularly when mediated by trust. Conversely, V. & Mathur (2022) identify perceived risk as the most significant barrier to adoption among farmers globally, while simultaneously confirming the positive influence of perceived usefulness, trust, and social factors - with demographic characteristics serving as important moderators. Xie et al. (2021) advance theoretical understanding by integrating perceived risk and value into an enhanced UTAUT framework, revealing that performance and effort expectations indirectly affect adoption through their impact on perceived value. Contrasting these findings, Meyliana et al. (2019) found perceived risk to be statistically insignificant in the Indonesian context, where trust emerged as the primary determinant of perceived usefulness and adoption intention. These divergent results suggest that risk perception operates differently across user segments and cultural contexts, potentially depending on users' risk tolerance and familiarity with digital finance.

The literature underscores perceived cost as a critical yet understudied factor influencing FinTech adoption, operating alongside established determinants like ease of use and trust. Utami et al. (2021) systematically identify cost as an external barrier within their framework of consumer and firm-level adoption drivers, though they note its impact varies by market context. Firmansyah et al. (2022) extend this view by demonstrating that while TAM and UTAUT models dominate adoption research, cost-related constructs—such as transaction fees and infrastructure expenses—require deeper integration into theoretical frameworks, particularly in emerging economies. Hornuf et al. (2024) reveal that in Sub-Saharan Africa, perceived cost interacts with ease of use and usefulness, yet provider-side strategies (e.g., pricing models) remain under-researched despite their potential to mitigate adoption barriers. Kajol et al. (2022) explicitly rank cost among the top five adoption inhibitors, alongside risk and complexity, noting its disproportionate impact on low-income users and micro-enterprises.

The relationship between technology trust and FinTech adoption has been extensively examined in recent literature, revealing trust as a critical determinant of user acceptance. Jafri et al. (2023) conducted a comprehensive thematic analysis of banking behavioral intentions, identifying trust and security as among the most significant predictors of FinTech adoption, alongside performance expectancy and perceived usefulness. Hu et al. (2019) specifically highlight how perceived trust in mobile technology serves as a crucial facilitator of FinTech innovation adoption by reducing uncertainty, while simultaneously demonstrating how perceived risk can undermine this trust and create adoption barriers. Firmansyah et al. (2022) confirm these findings within the established Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks, while advocating for the inclusion of additional trust-related constructs to better capture evolving FinTech adoption patterns. The literature consistently positions trust as a multidimensional construct encompassing reliability, credibility, safety, and integrity of digital financial systems (Hu et al., 2019), with its importance magnified in comparison to traditional financial transactions.

In the context of Nepal, the literature reveals distinct patterns in FinTech adoption influenced by technological perceptions, demographic factors, and service quality. Rakhi et al. (2017) demonstrate that perceived risk, usefulness, ease of use, and peer influence significantly drive mobile banking adoption, though security concerns and self-efficacy create barriers, reflecting Nepal's evolving digital trust landscape. Chawla et al. (2017) segment Nepalese users into adoption leaders, followers, and laggards, highlighting widespread distrust in mobile banking despite varying attitudes, with followers particularly wary of data privacy—a critical insight for market segmentation strategies. Mathur et al. (2018) identify pronounced resistance among Nepal's geriatric population (65+ years), attributing low FinTech app adoption to usability challenges and generational technological disparities, underscoring the need for age-inclusive design. Gautam et al. (2023) emphasize that enhancing online banking service quality—especially website design, security, and privacy—directly improves e-customer satisfaction and loyalty in Nepalese commercial banks, suggesting institutional improvements can mitigate adoption barriers.

Research Hypothesis

The adoption of FinTech remains an underexplored phenomenon, with existing studies often examining isolated drivers in fragmented contexts. This study systematically evaluates how six critical independent variables—perceived usefulness, perceived ease of use, perceived risk, perceived awareness, perceived cost, and trust in technology—collectively influence the adoption of FinTech as the dependent variable. While prior research has addressed these factors individually, their integrated impact warrants rigorous examination to uncover potential synergies or trade-offs in user decision-making.

H_1: Perceived usefulness has no significant effect on the adoption of FinTech.

H_2: Perceived ease of use does not positively influence FinTech adoption.

H_3: Perceived risk does not negatively affect FinTech adoption.

H_4: Perceived awareness is not significantly associated with FinTech adoption.

H_5: Perceived cost does not hinder FinTech adoption.

H_6: Trust in technology has no measurable impact on FinTech adoption.

By testing these hypotheses, this study aims to disentangle the complex interplay of cognitive, behavioral, and economic factors shaping FinTech adoption, offering actionable insights for policymakers and service providers seeking to enhance digital financial inclusion.

Methodology:

Research methodology refers to a systematic process used to address challenges and develop knowledge about a specific discipline. It includes all aspects contributing towards achieving the research goals (Holme and Solvang, 1996). Moreover, research design is regarded as the backbone of the structured collection and analysis of data (Ghauri and Garonhaug; Bryman and Bell, 2007).

Research Design

This research study has employed descriptive and causal-comparative research designs to deal with the issues associated with factors affecting adoption of fintech in Nepal. The descriptive research design has been employed for facts finding and searching adequate information about the adoption of fintech in Nepal. It is used to describe the accurate results and further describe about the characteristics of the sample. Research design involves the systematic collection and presentation of data to give clear picture of a particular situation. This study also used causal comparative research design that helps to analyze the possible cause and effect

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relationship between various dependent and the independent variables. More specifically, the study examines the perceived usefulness, perceived ease of use, perceived risk, perceived awareness, perceived cost and trust in technology.

Target Population, Sample and Data Collection

Population of the study is all the Fintech User. The study adopted convenient sampling techniques and a sample size of 352 respondents while 70 questionnaires were used for the study. The data for the study were collected from the well-structured questionnaire entitled “Factors Affecting Adoption of Fintech in Nepal”. In this study there are six independent variables, namely perceived usefulness, perceived ease of use, perceived risk, perceived awareness, perceived cost and trust on technology. The adoption of fintech is the dependent variable. This section outlines briefly the research subject and object, variable operationalization, population and samples, the sampling method, and the statistical test applied in the research.

In order to accomplish this, the data collection tool of choice was a questionnaire, as this process was quicker and more cost-effective compared to some other processes like conducting interviews or brainstorming sessions (Bryman and Bell, 2007). Furthermore, since respondents were individual users, they are likely to have had little time to allow for interviews, making questionnaires the most reasonable method, as they could be filled out at the respondent’s own convenience.

The research used a sample of 700 closed-ended questionnaires distributed directly to Nepalese FinTech users. From these, 352 questionnaires were completed and analyzed, making the response rate 50.29%. The sample size was determined according to resource availability (time, human capital, financial resources, and the ability of researchers (Yamane 1967). According to Yamane (1967), collect data from at least 35 respondents or from 10% of the total sample size up to 10% of the sample size, which can produce valid results using statistical data analysis tools in quantitative research. This study used a convenient and purposive sampling method to collect the data.

Nature and Sources for the Study

Research hypotheses were tested against primary data. The distinction between primary and secondary data is primarily based on the purpose for which the data was collected (Jankowicz, 2003).

Model Specification

To analyze the relationship between the dependent and independent variables, an econometric model has been designed and implemented. This regression model provides the empirical framework for testing the proposed hypotheses.

The specified model is as follows:

$AF = \alpha + \beta_1 PU + \beta_2 PEU + \beta_3 PR + \beta_4 PA + \beta_5 PC + \beta_6 TT + \epsilon$

Where:

ϵ = Error term, accounting for unobserved factors affecting the dependent variable.

β_0 = Constant term, representing the intercept of the regression model.

$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ *and* β_6 represents coefficients of the explanatory variables, reflecting the magnitude and direction of their effects on the dependent variable.

This model serves as the foundation for assessing how these factors influence adoption of FinTech users.

Data Analysis Method

The questionnaire data were statistically analyzed for rigorous systematization. This part was a pilot test carried out to validate the research instrument, remove some items of the questionnaire with poor quality (missing values and biased), and refine the questionnaire. Data analysis was then undertaken using a range of statistical techniques, including Cronbach’s Alpha, descriptive statistics, correlational analysis, and regression analysis, to evaluate the instrument reliability, summarize the key characteristics of data, examine the association between variables, and test the research hypotheses.

Reliability Test

Cronbach's alpha is a commonly used measure in behavioral and social science research to assess internal consistency of measurement scales (Liu et al., 2010). Cronbach's alpha was used in this study to check the internal consistency of all the multi-item constructs measured in the survey on a five-point Likert scale.

Acceptable reliability was informed by established psychometric standards. According to Nunnally (1978), a Cronbach's alpha coefficient of at least 0.70 is considered acceptable for determination of adequate scale reliability. Some scholars, however, maintain that acceptable values are slightly higher than this, although the corrected item-total correlations must be at or above 0.30 (Shelby, 2011).

The analysis of reliability shows good internal consistency (Cronbach's alpha = 0.798 overall, values higher than usual references). In addition, all the alpha coefficients of the subscales were greater than 0.60, confirming the strength of the measurement tool.

Demographic Analysis

(The table indicates the descriptive statistics of the demographic variables i.e., Gender, age, Marital status, academic qualification and monthly spending to overview the characteristics of the respondents.)

Factors	Items	Frequency	Percentage
Gender	Female	172	48.9
	Male	178	50.6
Age	20 to 30	205	58.2
	30 to 40	59	16.8
	40 to 50	13	3.7
	50 and above	9	2.6
	Below 20	66	18.8
Marital Status	Married	107	30.4
	Single	244	69.3
Academic Qualification	Bachelor	140	39.8
	Masters	89	25.3
	Research Degree	10	2.8
	Secondary	113	32.1
Monthly Spending	Up to 10,000	86	24.4
	10,001 to Rs. 20,000	181	51.4
	Rs. 20,001 to Rs. 30,000	54	15.3
	Rs. 30,001 to Rs. 40,000	29	8.2
	Rs. 40,000 and above	2	0.6
Profession	Agriculturist	22	6.3
	Entrepreneur	30	8.5
	Service man	69	19.6
	Students	231	65.6

The demographic analysis reveals several key findings about the respondent profile. The sample was nearly evenly split by gender, with males (50.6%) slightly outnumbering females (48.9%). A majority of respondents (58.2%) fell within the 20-30 age bracket, followed by those below 20 (18.8%), indicating a predominantly young population. Marital status data showed that most participants were single (69.3%), aligning with the younger age distribution. Academically, the largest proportion held a bachelor's degree (39.8%), followed by secondary education (32.1%) and master's degrees (25.3%). Monthly spending patterns indicated that over half (51.4%) spent between Rs. 10,001-20,000, while only 0.6% spent above Rs. 40,000. Professionally, students constituted the majority (65.6%), followed by service professionals (19.6%), reflecting a sample heavily weighted toward younger, less established individuals.

Descriptive Analysis

(This table presents mean, median, standard deviation, minimum, maximum values of the 352 sample. Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Risk (PR), Perceived Awareness (PR), Perceived Cost (PC), Trust on Technology (TT) and Adaption of Fintech (AF).)

Variable	Minimum	Maximum	Mean	Median	Std. Deviation
PU	1.0	6.72	2.44	2.13	1.02
PEU	1	5	2.22	2.14	0.651
PR	1	5	2.30	2.22	0.576
PA	1	5	2.30	2.29	0.622
PC	1	5	2.36	2.33	0.55
TT	1	5	2.24	2.17	0.668
AF	1.0	8.0	2.457	2.000	1.2719

The descriptive statistics reveal key insights into respondents' perceptions of fintech adoption. Perceived Usefulness (PU) exhibited the widest range (1.0–6.72) and highest mean (2.44), suggesting variability in how beneficial users find fintech, though the median (2.13) indicates a generally moderate perception. Perceived Ease of Use (PEU) and Trust in Technology (TT) displayed lower means (2.22 and 2.24, respectively) with relatively small standard deviations (0.651 and 0.668), implying consistent but cautious agreement on usability and trust. Perceived Risk (PR), Awareness (PA), and Cost (PC) clustered closely around means of 2.30–2.36, with tight dispersion (SDs: 0.55–0.622), reflecting neutral to slightly positive perceptions. Adoption of Fintech (AF) had the highest maximum value (8.0) but a median of 2.00, indicating some outliers or extreme responses skewing the mean (2.457). Overall, the data suggest moderate fintech acceptance, with perceived usefulness being the most variable factor, while other constructs demonstrate relatively uniform, albeit reserved, user attitudes.

Correlational Analysis

(This table shows the bivariate Pearson's Correlation Coefficient between different pairs of variables used in the study for the analyzing the oversubscription with 352 observations. Here Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Risk (PR), Perceived Cost (PC), Trust in Technology (TT), and Adoption of Fintech (AF) Correlation are examined.)

Correlations							
	PU	PEU	PR	PA	PC	TT	AF
PU	1						
PEU	.393**	1					
PR	.606**	.737**	1				
PA	.359**	.942**	.722**	1			
PC	.427**	.786**	.801**	.768**	1		
TT	.349**	.683**	.711**	.583**	.714**	1	
AF	.673**	.320**	.509**	.277**	.339**	.273**	1
** Correlation is significant at the 0.01 level (2-tailed).							

*Note(s): * indicates that correlation is significant at 0.05 percent level (one tailed) and '**' indicates that correlations is significant at 0.01 percent level (one tailed).*

The correlational analysis reveals significant relationships among key variables influencing fintech adoption. Perceived Usefulness (PU) exhibits a strong positive correlation with Adoption of Fintech (AF) ($r = 0.673$, $p < 0.01$), suggesting that users who find fintech beneficial are more likely to adopt it. Perceived Ease of Use (PEU) shows the strongest association with Perceived Awareness (PA) ($r = 0.942$, $p < 0.01$), indicating that ease of use significantly enhances user awareness. Perceived Risk (PR) is highly correlated with PEU ($r = 0.737$, $p < 0.01$) and PC ($r = 0.801$, $p < 0.01$), implying that risk perceptions are closely tied to usability and cost concerns. Trust in Technology (TT) is moderately correlated with PR (r = 0.711, p < 0.01) and PC (r = 0.714, p < 0.01), reinforcing the interplay between trust, risk, and cost in fintech adoption. Notably, AF has weaker but still significant correlations with PEU (r = 0.320), PR (r = 0.509), and PC (r = 0.339), highlighting that while these factors influence adoption, PU remains the strongest predictor. Overall, the findings underscore the multidimensional nature of fintech adoption, where usability, risk, cost, and trust collectively shape user decisions.

Regression Analysis

The results are based on 352 observations using linear regression model. The model is AF = α + β1 PU + β2 PEU+ β3 PR + β4 PA+ β5 PC + β6TT +e., AF (Adaption of Fintech) is the dependent variables and PU (Perceived Usefulness), PEU (Perceived Ease of Use) PR (Perceived Risk), PA (Perceived Awareness), PC (Perceived Cost) and TT (Trust on Technology) are the independent variables. Estimated beta coefficient from ordinary list squares regression of Adaption of Fintech has been drawn. In parenthesis t statistics are presented.

Model	Constant	PU	PEU	PR	PA	PC	TT	R^2	F- Ratio
1	-0.55 (-25.89)	1.23*** (151.95)						0.985	23,089.74*** (0.00)
2	1.071 (4.681)		0.62*** (6.3)					0.102	39.85*** (0.00)
3	-0.132 (-0.546)			1.13*** (0.10)				0.259	122.59*** (0.00)
4	1.152 (4.596)				0.57*** (11.07)			0.077	29.13*** (0.00)
5	0.618 (2.204)					0.78*** (6.737)		0.115	45.383*** (0.00)
6	1.292 (5.653)						0.520*** (5.317)	0.075	28.274*** (0.00)
7	0.296 (-12.21)	1.27*** (184.78)	0.16*** (14.9)					0.99	19,037.26*** (0.00)
8	-0.08 (-7.94)	1.34*** (413.24)	0.01 (1.64)	0.33*** (42.06)				0.99	77,604.55*** (0.00)
9	-0.05 (-5.58)	1.34*** (519.9)	0.14*** (13.86)	-0.32*** (-50.3)	-0.15*** (-14.67)			0.99	94,094.81*** (0.00)
10	-0.025 (-2.89)	1.340*** (565.79)	0.15*** (16.49)	-0.29*** (-43.77)	-0.143*** (-15.43)	-0.05*** (-8.26)		0.99	89,856.91*** (0.00)
11	-0.018 (-2.30)	1.34*** (615.673)	0.067*** (4.20)	-0.31*** (-48.53)	-0.31*** (-14.98)	-0.002 (0.008)	0.22*** (-0.25)	0.99	91,500.93*** (0.00)

*Note(s): Three***, two ** and one * asterisks indicate statistical significance at 1%, 5% and 10% level respectively.*

The regression analysis reveals that Perceived Usefulness (PU) has the strongest positive impact on Adoption of Fintech (AF), with highly significant coefficients (β = 1.23 to 1.34, p < 0.01) across all models, indicating that users who perceive fintech as beneficial are far more likely to adopt it. Perceived Ease of Use (PEU) also contributes positively to adoption (β = 0.16 to 0.62, p < 0.01), though its influence weakens when other variables are introduced, suggesting that usability alone is not sufficient to drive fintech usage. Perceived Risk (PR) negatively affects adoption (β = -0.29 to -0.33, p < 0.01), demonstrating that heightened risk perceptions act as a deterrent to fintech acceptance. Contrary to expectations, Perceived Awareness (PA) and Perceived Cost (PC) exhibit negative relationships with adoption (β = -0.15 to -0.31, p < 0.01), implying that greater awareness or cost concerns may paradoxically reduce willingness to use fintech services. Trust in Technology (TT) has a modest but statistically significant positive effect (β = 0.22, p < 0.01), reinforcing that user trust enhances fintech adoption, albeit to a lesser extent than PU or PEU. The models explain an exceptionally high proportion of variance ($R^2 = 0.985–0.99$), confirming their robustness in predicting fintech adoption behavior. The extremely high F-statistics (all $p < 0.01$) further validate the overall significance of the regression models, indicating that the independent variables collectively have a strong explanatory power. The dominance of PU across all specifications suggests that functional benefits are the primary driver of fintech adoption, outweighing other factors. The negative coefficients for PR, PA, and PC highlight potential barriers that fintech providers must address to encourage wider acceptance. Finally, the incremental addition of variables in Models 7–11 demonstrates how different factors interact, with PU remaining the most stable predictor, while other variables exhibit varying degrees of influence depending on model specification. These findings provide critical insights for fintech developers and policymakers seeking to enhance adoption through targeted improvements in usability, risk mitigation, and cost-effectiveness.

Hypothesis Testing Result

Hypothesis	Statement	Results	Remarks	Conclusion
H_1	Perceived usefulness has no significant effect on the adoption of FinTech.	($\beta = 1.23$ to 1.34^{***}, $p < 0.01$)	Rejected	Perceived usefulness has a strong positive effect on FinTech adoption.
H_2	Perceived ease of use does not positively influence FinTech adoption.	($\beta = 0.16$ to 0.62^{***}, $p > 0.05$	Rejected	Perceived ease of use positively influences adoption, though its effect diminishes when other factors are controlled.
H_3	Perceived risk does not negatively affect FinTech adoption.	($\beta = -0.29$ to -0.33^{***}, $p < 0.01$).	Rejected	Perceived risk negatively affects adoption, confirming it as a barrier.
H_4	Perceived awareness is not significantly associated with FinTech adoption.	$\beta = -0.15$ to -0.31^{***} ($p > 0.01$)	Rejected	Perceived awareness is negatively associated with adoption (counterintuitive; may reflect over-awareness of risks).
H_5	Perceived cost does not hinder FinTech adoption.	$\beta = -0.002$ to -0.31^{***} ($p < 0.01$)	Rejected	Perceived cost sometimes hinders adoption, but its impact is inconsistent.
H_6	Trust in technology has no measurable impact on FinTech adoption.	$\beta = 0.22^{***}$ ($p < 0.01$)	Rejected	Trust in technology has a modest but significant positive impact on adoption.

Summary and Conclusion

The analysis reveals that Perceived Usefulness (PU) is the most robust predictor of FinTech adoption, with consistently high positive coefficients ($\beta = 1.23–1.34$, $p < 0.01$), underscoring its critical role in user acceptance. Perceived Ease of Use (PEU) also significantly influences adoption, though its impact diminishes when controlling for other variables, suggesting usability alone is insufficient without tangible benefits. Perceived Risk (PR) exhibits a strong negative effect ($\beta = -0.29$ to -0.33, $p < 0.01$), confirming security and privacy concerns as major adoption barriers. Counterintuitively, Perceived Awareness (PA) correlates negatively with adoption ($\beta = -0.15$ to -0.31, $p < 0.01$), possibly reflecting heightened risk awareness rather than familiarity benefits. Perceived Cost (PC) shows mixed effects, occasionally deterring adoption, while Trust in Technology (TT) has a modest but significant positive influence ($\beta = 0.22$, $p < 0.01$). The high explanatory power of the models ($R^2 = 0.985–0.99$) and significant F-statistics validate the collective strength of these factors in predicting adoption behavior. These findings highlight the need for FinTech providers to prioritize functional utility (PU) and risk mitigation (PR) while refining usability (PEU) and trust (TT) to enhance adoption. Policymakers and developers should also address the paradoxical role of awareness through targeted education to align user perceptions with actual benefits, ensuring broader financial inclusion.

Limitation

There are also certain limitations of this study that need to be kept in mind while assessing the results. The study is based on 352 observations, which may not be sufficiently large or diverse to represent the broader population. The sample is not representative of the general population the findings may not be generalizable to different demographic groups or regions. The data were collected through surveys or questionnaires, there could be biases such as social desirability bias, where respondents might overstate their perceived usefulness or ease of use of fintech to align with what they perceive as socially acceptable or desirable. The study is cross-sectional, it only shows a single point in time, so it can't prove cause and effect. While it can find strong links between variables, it's hard to tell if perceived usefulness actually leads to fintech adoption or if something else might be influencing both. Finally, the number of variables considered in the model, including perceived usefulness, perceived ease of use, perceived risk, perceived awareness, perceived cost and trust on technology restricts the scope of the analysis. The inclusion of moderating and control variables could potentially refine the model.

Future Research and Implication

This study provides several interesting opportunities for future research and offers important implications for theory and practice. To enhance FinTech adoption in Nepal, providers should prioritize communicating practical benefits while strengthening security measures and user-friendly designs to address perceived risks and usability barriers. Targeted financial literacy programs and transparent grievance mechanisms should be implemented to build trust, particularly among rural populations and SMEs. Future research should expand beyond individual users to examine commercial adoption patterns, incorporating advanced analytical methods like non-linear modeling and machine learning to better capture adoption dynamics. Studies could also investigate how emerging technologies like blockchain and AI might transform Nepal's FinTech landscape, while assessing infrastructure gaps that hinder rural inclusion. Comparative analyses of urban versus rural adoption disparities would help develop geographically tailored solutions, complemented by longitudinal studies tracking adoption trends post-policy interventions. Additionally, researchers should explore the bidirectional relationship between financial literacy and FinTech usage, employing mixed-methods approaches that combine qualitative insights with robust econometric models. Finally, integrating secondary data from NRB and FinTech platforms could validate findings while revealing macroeconomic influences on adoption, creating a more comprehensive understanding of Nepal's digital finance evolution. These combined efforts would bridge existing knowledge gaps while informing policies and business strategies for inclusive FinTech growth.

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