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# What Drives Fintech Adoption? A Study Of Financial Literacy's Moderating Role In India

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***Abstract***
*This study meticulously examines the principal drivers of FinTech adoption in India, with a particular emphasis on the moderating influence of financial literacy. Utilizing the Technology Adoption Model (TAM), it identifies critical factors that shape FinTech adoption behaviours. Data were meticulously collected from 399 respondents across various Indian states through an online Google form and analysed employing SmartPLS 3.3 path modelling. The findings reveal that social influence and transaction processes exhibit significant positive correlations with FinTech adoption, whereas rewards and trust appear to have negligible effects on adoption decisions. Financial literacy emerges as a pivotal moderating variable, enhancing the favourable influences of perceived ease of use and perceived usefulness on adoption outcomes. These insights carry profound implications for stakeholders, delineating strategies to bolster adoption and address disparities in financial inclusion across diverse user segments in India.*
***Keywords:*** *FinTech , Financial literacy, TAM, FinTech adoption, Perceived ease of use, Perceived usefulness*

## 1.INTRODUCTION

The swift advancement of innovative technologies, coupled with the exponential growth of the internet, has catalyzed substantial growth in traditional industries across India. The term "Financial Technology," or FinTech, was first articulated by Citicorp in 1993 during the Financial Services Technology Consortium; however, it became a fixture in public discourse in 2014 (Pedersen, 2015). FinTech encompasses the application and integration of cutting-edge financial technologies—including blockchain, big data, artificial intelligence (AI), cloud computing, quantum computing, and machine learning—to refine and elevate the financial sector (Darolles, 2016). It represents revolutionary business models informed by digital technologies that disrupt existing industry frameworks and traditional business practices, greatly enhancing access to financial services and transforming product and service delivery mechanisms.

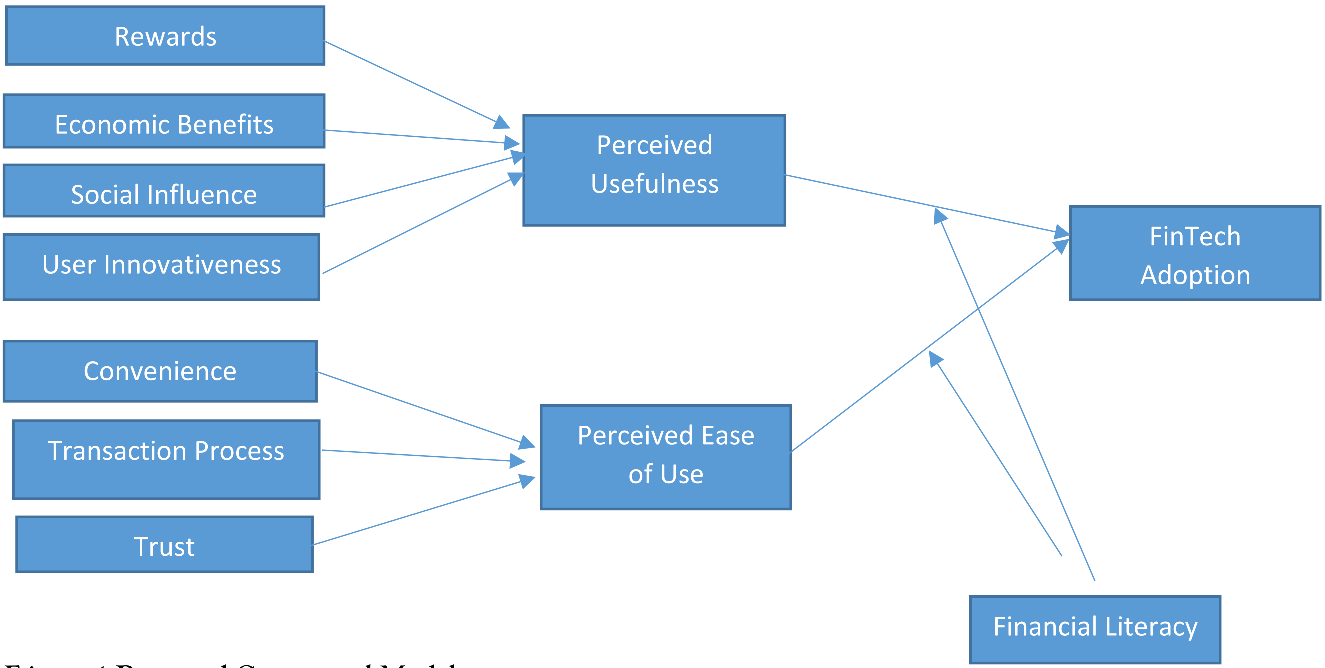
Additionally, FinTech fosters a fertile environment for innovative entrepreneurship and intensifies competition among commercial banks and financial institutions. Prominent FinTech services, such as peer-to-peer lending, crowdfunding, InsurTech, and WealthTech, leverage technologies like blockchain, machine learning, and AI. Financial institutions are increasingly adopting these innovations to achieve cost reductions, thereby minimizing expenditure on customer acquisition, risk management, and operational activities. The effective implementation of FinTech solutions within the banking sector enhances profitability and bolsters employee efficiency by offering customers a diverse array of innovative service options (Ky et al., 2019).

While there is no universally accepted definition of FinTech, three discernible perspectives have emerged: the demand side, supply side, and regulatory side. The Financial Stability Board (FSB, 2017) defines FinTech as an aggregation of innovative technology providers dedicated to delivering swift and seamless services. Demand-side drivers of financial innovation derive from elevated expectations surrounding convenience, cost, speed, and user-friendliness (FSB, 2017), culminating in technology-driven financial services. Conversely, on the supply side, FinTech is recognized as the confluence of financial services and technological advancement, enhancing the financial ecosystem by introducing a broad spectrum of new financial services to the market. This evolution positions FinTech firms as both competitors and complements to traditional financial intermediaries, representing a disruptive innovation that poses competitive threats to established entities while simultaneously offering enhanced flexibility and efficiency in financial service delivery. From a regulatory standpoint, FinTech has broadened access to financial services in previously underserved regions, fortifying the nation's financial inclusion initiative through the introduction of innovative offerings. However, the rapid expansion of FinTech also presents new challenges, including cybersecurity threats and financial instability.

The global proliferation of the internet and mobile technology has significantly influenced technological integration within financial services, reshaping consumer habits and preferences. During the COVID-19 pandemic, India observed a marked acceleration in digital transactions, predominantly facilitated by the FinTech sector, which enabled seamless digital interactions via online platforms. According to E&Y (2017), one-third of Indian consumers actively engage with at least two FinTech services, including deposits, money transfers, investments, and fundraising for startups. As FinTech enterprises continue to expand rapidly, they pose a disruptive challenge to traditional financial institutions, which must cultivate their own FinTech capabilities to remain competitive. Alarmingly, 83% of conventional financial service providers acknowledge the existential risks posed by emerging FinTech start-ups (Muthukannan et al., 2020). FinTech companies deliver services characterized by convenience, speed, and cost-effectiveness, capturing 82% of revenues from established incumbents. India ranks second globally with an 84% adoption rate of FinTech-based services. While numerous studies have previously explored FinTech adoption, very few have targeted the Indian context specifically. Significantly, this study is trailblazing in analysing the moderating influence of financial literacy on FinTech adoption. An adept understanding of financial literacy is critical in shaping individuals' finance-related decisions, encompassing wealth management, investment strategies, saving habits, and retirement planning.

### 1.1Fin Tech Evolution

The traditional banking model has transitioned from simple deposits, loans, and physical branches to an era characterized by mobile banking




**F igure-1 Proposed Conceptual Model**

### 2.2 Hypothesis Development

**1.Perceived Usefulness:**

As defined by the Technology Adoption Model (Davis et al., 1989), perceived usefulness encapsulates users' belief in the extent to which a technological innovation enhances their performance relative to conventional methods. Thakor et al. (2020) further elaborate that it pertains to an individual's perception of the advantages offered by a technology-driven product or service. Recognized as a pivotal determinant in shaping users' behavioural intentions and adoption decisions, perceived usefulness has been extensively studied. A substantial body of research underscores its significant influence on the willingness to adopt innovative technologies (Chen et al., 2021; Shaikh et al., 2020; Firmansyah et al., 2020). Drawing upon empirical findings, existing literature indicates that a higher perceived usefulness substantially increases the likelihood of users embracing technological advancements (Elhajjar & Ouaida, 2019; Singh et al., 2020).

Hypothesis: **H1:** Perceived usefulness exerts a significant positive influence on FinTech adoption.

**2. Perceived Ease of Use(PEOU):**

Davis (1989) defines perceived ease of use as "the extent to which a user believes that utilizing a particular technology will be effortless." Numerous empirical studies corroborate the relationship between PEOU and technology adoption intention (Shaikh et al., 2020; Singh et al., 2020; Windasaria et al., 2022; Setiawan et al., 2021; Singh & Sharma, 2022). Windasaria et al. (2022), employing a sequential mixed-methods approach suggested by Creswell (2009), discovered that perceived ease of use significantly enhances the adoption of digital banking services. Similarly, Singh and Sharma (2022), through structural equation modelling in the Indian context, identified PEOU as a crucial factor influencing FinTech payment services among Millennials and Gen X. Furthermore, Shaikh et al. (2020) established a direct correlation between PEOU and the acceptance of FinTech-based Malaysian banking services. These findings collectively affirm that perceived ease of use fosters FinTech adoption.

Hypothesis: **H2:** Perceived ease of use has a significant positive influence on FinTech adoption.

**3.Rewards:**

Rewards function as strategic incentives to encourage the adoption of FinTech services (Lepper & Greene, 2015). These incentives, typically in the form of cashback or reward points, are directly credited to users' accounts, enhancing their engagement with FinTech services. Windasari et al. (2022b) assert that extrinsic rewards such as monetary benefits significantly contribute to customer satisfaction and behavioural intention.

Hypothesis:

**H3:** Rewards are positively related to perceived usefulness.

**4.Economic Benefit:**

FinTech services often provide a cost-effective alternative to traditional financial intermediaries. Economic benefit, regarded as an extrinsic motivator (Dodds et al., 1991; Mackenzie, 2015), entails a trade-off between financial cost reduction and monetary gain derived from FinTech usage (Mackenzie, 2015; Jain & Raman, 2022). Services such as P2P lending, digital borrowing, and insurance confer financial advantages to users.

Hypothesis: **H4:** Economic benefit is positively related to perceived usefulness.

**5.Social Influence:**

Social influence plays a crucial role in the adoption of technological innovations, including FinTech. It encompasses societal, familial, and peer pressures that shape individuals' adoption decisions. Prior studies (Singh et al., 2020; Windasari et al., 2022; Basri et al., 2022) highlight the varying degrees of influence exerted by referents. As an essential determinant of technology adoption, social influence shapes user perceptions and behaviours.

Hypothesis: **H5:** Social influence is positively related to perceived usefulness.

**6. User Innovativeness (UI):**

User innovativeness reflects an individual's propensity to embrace novel technological solutions. Yun et al. (2020) emphasize that both personal knowledge and external information accelerate the likelihood of adopting innovative technologies. Furthermore, UI has been recognized as a significant predictor of technology acceptance (Lu et al., 2005; Ciftci et al., 2021; Son & Han, 2011; Ullah et al., 2020).

Hypothesis: **H6:** User innovativeness is positively related to perceived usefulness.

**7.Convenience:**

Convenience, an extrinsic motivator, enhances FinTech adoption by ensuring accessibility and operational flexibility (Kuo & Teo, 2015). The ease of use of FinTech services, particularly in terms of time and location adaptability, significantly enhances user comfort (Okazaki & Mendez, 2013).

Hypothesis: **H7:** Convenience is positively related to perceived ease of use.

**8. Transaction Process:**

A streamlined transaction process is a fundamental advantage of FinTech services. It reduces time and costs, thereby influencing adoption decisions (Chishti, 2016). Furthermore, secure databases ensure data confidentiality, fostering trust among users (Suzianti et al., 2021). Enhanced financial efficiency, facilitated by seamless transactions, contributes to FinTech adoption (Zavolokina et al., 2016).

Hypothesis: **H8:** The transaction process is positively related to perceived ease of use.

**9.Trust:**

Given the financial nature of FinTech services, trust remains a cornerstone of adoption. Users are particularly concerned about data privacy and security risks (Chong, 2013). Establishing trust at the early stages of adoption enhances continued usage (Slade et al., 2015; Shareef et al., 2018). Trust significantly influences users' technology adoption decisions (Cao et al., 2018; Kuriyan & Ray, 2009; Kuriyan et al., 2010).

Hypothesis: **H9:** Trust has a positive relationship with perceived ease of use.

**10. Financial Literacy (FL):**

Financial literacy pertains to individuals' comprehension of financial concepts such as inflation, GDP, compound interest, and investment planning (Setiawan et al., 2021; Lusardi, 2019). Prior studies suggest that financial literacy positively impacts FinTech adoption (Andreou & Anyfantaki, 2021; Morgan & Thinh, 2020; Grabner-Krauter & Faullant, 2008). It is a key global policy focus (OECD, 2018), given its role in enhancing financial decision-making.

Hypotheses: **H10a:** Financial literacy moderates the relationship between perceived usefulness and FinTech adoption.

**H10b:** Financial literacy moderates the relationship between perceived ease of use and FinTech adoption.

## 3. METHODOLOGY

### 3.1Measures

This study employs a quantitative research approach to examine the determinants of FinTech adoption across various Indian states. The survey questionnaire was designed based on the TAM framework, incorporating constructs related to perceived utility, ease of use, and FinTech adoption.

### 3.2 Survey Instrument Development:

The survey instrument was formulated through extensive discussions with academic and industry experts specializing in FinTech. The questionnaire, structured in two sections, includes demographic details (age, gender, income, education, marital status, and residential state) and variable-specific metrics. Data were gathered from 450 respondents, yielding 399 valid responses measured on a Likert scale (1 = strongly disagree, 5 = strongly agree). The analysis employed Structural Equation Modelling (SEM) to validate hypotheses and assess model reliability, offering insights into FinTech adoption drivers and barriers.

| No. | Construct Name | Scale adapted |
|---|---|---|
| 1 | Perceived Usefulness | Chen et. al (2021), Wen-Lung et. Al(2020), Sethiawan et al (2021), Firmansyah et. Al(2023), Shaikh et. Al(2019) |
| 2 | Perceived Ease of Use | Nugraha et. Al(2022), Sethiawan et. Al (2021), Windasaria et al(2022),Shaikh et. Al(2019) |
| 3 | FinTech Adoption | Suzianti et al. (2021), Ali et al. (2021c), S. Singh et al. (2020), Huarng and Yu (2022), Chan et al. (2022) |
| 4 | Financial Literacy | Chan et.al (2022), Kakinuma(2021), Firmansyah(2023), Jünger(2019), Setiawan et. Al, Panayiotis & Anyfantaki(2020) |
| 5 | User innovativeness | Shaikh et. Al(2019), (Shaikh et al., 2020b), (Setiawan et al., 2021b) |
| 6 | Convenience | Jain & Raman(2021),Suzianti(2020),Ali et. Al(2021),Ryu Hyun-Sun(2018) |
| 7 | Transaction Process | Ali et. Al(2021), ,Ryu Hyun-Sun(2018) |
| 8 | Economic Benefit | Ali et. Al (2021), Suzianti(2020), Jain & Raman(2021),Ryu Hyun-Sun(2018) |
| 9 | Trust | (Ali et al., 2021b), Savitha et. Al(2022) |
| 10 | Rewards | Windasaria et al(2022) |
| 11 | Social Influence | Oladapo et. Al(2020), Singh et. Al(2020), Windasaria et. Al(2022), Savitha et. Al(2022), Bajunaieda et. Al( ), Firmansyah et. Al(2023), Savitha et. Al (2022), Chan et. Al(2022),Shaikh et. Al(2019) |

**Table-1 Variables Description**

### 3.3 Data Collection

For collecting data, the researcher shared a structured questionnaire electronically using Google Forms. The distribution targeted faculty members from various Indian universities across multiple states, they were specifically selected for their academic affiliation and familiarity with FinTech services. They were asked to share this survey form with their students through official university groups to ensure wider coverage and better representation of the target demographic. The respondents thus included a mix of faculty members and students, primarily comprising individuals who had previous experience or usage of FinTech services. This approach combined convenience sampling to reach accessible participants and random sampling to enhance diversity within the sample. Data were gathered from 450 respondents, yielding 399 valid responses measured on a Likert scale (1 = strongly disagree, 5 = strongly agree).

### 3.4 Sample Characteristics

The sample reflects a higher representation of younger individuals, particularly in the 18–25 age group (64.4%), which may indicate their greater engagement or interest in FinTech adoption. This could be due to factors such as increased digital adoption, financial awareness. The 26–35 age group (20%) forms the second largest segment, possibly representing early-career professionals or individuals exploring financial independence. The proportion of respondents decreases in the older age brackets, with 11% in the 36–45 age group and only 5% aged 46 and above, which could be attributed to lower digital engagement or reduced participation in survey-based research. Additionally, the gender distribution, with 59.40% male and 40.60% female respondents, may suggest varying levels of accessibility, interest, or representation in the study's domain.

**Table-2 Sample demographics**

| Variable | Observed Frequency | Response rate(%) | Variable | Observed Frequency | Response rate(%) |
|---|---|---|---|---|---|
| **Gender** | 399 | 100% | **Education** | 399 | |
| Male | 237 | 59.40% | Higher Secondary | 39 | 9.77% |
| Female | 162 | 40.60% | UG/Diploma | 117 | 29.3% |
| **Age(Year)** | 399 | | PG | 174 | 43.6% |
| 18-25 | 257 | 64.4% | Professional Degree | 69 | 17.29% |
| 26-35 | 80 | 20% | **Income(Monthly)** | 399 | |
| 36-45 | 42 | 11% | Below 30,000 | 252 | 63.16% |
| 46 & above | 20 | 5% | 31000 – 50000 | 82 | 20.55% |
| **Marital Status** | 399 | | 51000 – 70000 | 21 | 5.26% |
| Married | 94 | 23.56% | 71000 & above | 44 | 11.03% |
| Unmarried | 305 | 76.44% | | | |

## 4. RESULTS

To investigate the connections between different exogenous and endogenous variables, structural equation modeling, was applied. The measurement model and the structural model were the two parts of the analysis. While the structural model describes the causal relationships between independent and dependent variables, the measurement model establishes the relationship between latent constructs and their observed indicators (Chin, 1998; Gefen et al., 2000; Hair et al., 2014).

SEM is a potent analytical method for evaluating hypotheses incorporating both observable and latent variables (Bollen 1989). Furthermore, SEM's ability to evaluate intricate variable interactions makes it particularly appropriate for models with many indicators and latent dimensions, as noted by Anderson and Gerbing (1988).

### 4.1 Output of Measurement Model

**Table-3 Items reliability, internal consistency, convergent validity of measurement model**

| Constructs | Items | Outer Loading | AVE | CR | Cronbach alpha |
|---|---|---|---|---|---|
| PU | PU1: Fintech reduces financial service time. | 0.883 | 0.759 | 0.926 | 0.894 |
| | PU2: Fintech breaks the location limitation of financial services. | 0.849 | | | |
| | PU3: Using Fintech improves my performance in managing personal finances | 0.852 | | | |
| | PU4: Overall, Fintech services are useful to me | 0.901 | | | |
| SI | SI1: My family believes that using FinTech will provide better banking services | 0.845 | 0.770 | 0.910 | 0.851 |
| | SI2: My colleagues consider that using FinTech is convenient. | 0.883 | | | |

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| | | | | | |
|---|---|---|---|---|---|
| | SI3: My friends think that FinTech is better than traditional banking System | 0.905 | | | |
| EB | EB1: Using Fintech is cheaper than using conventional financial services | 0.860 | 0.759 | 0.904 | 0.842 |
| | EB2: I can save money when I use Fintech base services. | 0.854 | | | |
| | EB3: I can use various financial services at low-cost when I use Fintech based services. | 0.900 | | | |
| RWD | RWD1: I like to use Fintech services because it gives me many rewards. | 0.884 | 0.768 | 0.908 | 0.851 |
| | RWD2: I like to use Fintech services because I feel that I have save money from the rewards. | 0.845 | | | |
| | RWD3: Using Fintech services are very profitable for me. | 0.898 | | | |
| UI | UI1: When I hear about a new FinTech service, I look for ways to try it. | 0.910 | 0.779 | 0.913 | 0.806 |
| | UI2: Among my peers, I am usually the first one to try a new FinTech service. | 0.838 | | | |
| | UI3: I like to experiment with new Fintech services. | 0.898 | | | |
| PEOU | PEOU1: I think the operation interface of Fintech is friendly and understandable | 0.900 | 0.804 | 0.942 | 0.919 |
| | PEOU2: I expect the FinTech based services are easy to use. | 0.905 | | | |
| | PEOU3: I expect it will be easy for me to become skillful at using FinTech services. | 0.888 | | | |
| | PEOU4: Learning to use digital banking will be easy. | 0.892 | | | |
| CON | CON1: I can use financial services very quickly when I use Fintech. | 0.919 | 0.853 | 0.914 | 0.914 |
| | CON2: I can access financial services easily and comfortably when using Fintech services. | 0.941 | | | |
| | CON3: I can access financial services anywhere and anytime with Fintech | 0.909 | | | |
| TP | TP1: I can control my finances without needing to go to a bank when using Fintech services | 0.878 | 0.787 | 0.946 | 0.909 |
| | TP2: I can access various types of financial services simultaneously using Fintech | 0.912 | | | |
| | TP3: The process of borrowing and lending money through Fintech is easier and faster | 0.890 | | | |
| | TP4: I can perform peer-to-peer transactions between providers and users without having to go through intermediaries (such as banks). | 0.867 | | | |
| T | T1: I believe in our financial security when using Fintech services. | 0.909 | 0.809 | 0.927 | 0.883 |
| | T2: I believe that our personal information is protected when using Fintech services. | 0.889 | | | |
| | T3: In general, I believe that Fintech services can be trusted. | 0.900 | | | |
| FL | FL1: I have knowledge of compounding interest, inflation and GDP. | 0.892 | 0.814 | 0.929 | 0.885 |
| | FL2: I have knowledge of investment option such as SIP, Mutual Fund. | 0.907 | | | |

| | | | | | |
|---|---|---|---|---|---|
| | FL3: I understand financial planning and saving. | 0.906 | | | |
| FA | FA1: I haven't used but would like to use Fintech services soon | 0.715 | 0.720 | 0.927 | 0.901 |
| | FA2: I will be attracted to the bank that provides FinTech services | 0.859 | | | |
| | FA3: I will feel comfortable when I use FinTech services in the future | 0.893 | | | |
| | FA4: I will continue using Fintech service. | 0.906 | | | |
| | FA5: I strongly recommend the use of FinTech services | 0.855 | | | |

The measurement model assessment, as part of factor analysis, was conducted to evaluate the relationships between observed variables and their underlying latent constructs. This assessment was done through three key parameters: indicator reliability, convergent validity, and discriminant validity (Coltman et al., 2008; Hair et al., **2011**).

First, the indicator reliability was evaluated through the values of outer loadings. The loadings of indicators were consistently above the threshold value of 0.7, as demonstrated in Table 3. This indicates strong reliability of the indicators. For instance, the outer loadings for the construct PU (Perceived Usefulness) ranged from 0.849 to 0.901, all of which significantly exceed the 0.7 threshold. This consistency across indicators confirms the robustness of the measurement model.

**Table-4 Discriminant Validity**

| | Con | EB | FL | FA | PEOU | PU | RWD | SI | TP | T | UI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Con** | 0.923 | | | | | | | | | | |
| **EB** | 0.601 | 0.871 | | | | | | | | | |
| **FL** | 0.657 | 0.521 | 0.902 | | | | | | | | |
| **FA** | 0.687 | 0.564 | 0.637 | 0.848 | | | | | | | |
| **PEOU** | 0.811 | 0.631 | 0.568 | 0.644 | 0.896 | | | | | | |
| **PU** | 0.629 | 0.589 | 0.465 | 0.490 | 0.594 | 0.871 | | | | | |
| **RWD** | 0.498 | 0.591 | 0.430 | 0.483 | 0.521 | 0.444 | 0.876 | | | | |
| **SI** | 0.683 | 0.689 | 0.565 | 0.588 | 0.641 | 0.639 | 0.515 | 0.878 | | | |
| **TP** | 0.777 | 0.598 | 0.647 | 0.656 | 0.782 | 0.575 | 0.431 | 0.605 | 0.887 | | |
| **T** | 0.625 | 0.549 | 0.597 | 0.652 | 0.606 | 0.421 | 0.496 | 0.524 | 0.655 | 0.899 | |
| **UI** | 0.548 | 0.471 | 0.474 | 0.478 | 0.525 | 0.464 | 0.600 | 0.479 | 0.495 | 0.521 | 0.883 |

Discriminant validity has been confirmed by evaluating the values of the square root of the Average Variance Extracted (AVE) and their inter-construct correlations, following the methodology outlined by Fornell and Larcker (1981). Discriminant validity is essential as it measures the extent to which a construct is truly distinct from other constructs, ensuring that each construct represents a unique concept. According to Hair et al**. (2012)**, this assessment is crucial for validating the distinctiveness of constructs in the model. In this analysis, discriminant validity was assessed by comparing the square root of the AVE for each construct with the inter-construct correlations. As depicted in Table 4, the off-diagonal values represent the inter-construct correlations, while the diagonal values represent the square roots of the AVE. For example, the diagonal value for the construct CON (Convenience) was 0.923. This value is significantly higher than the inter-construct correlations, such as its correlation with PEOU (Perceived Ease of Use), which was 0.811. The fact that the diagonal value exceeds the off-diagonal values confirms the discriminant validity of the construct.

**4.2 Structural Model results**

The evaluation of the structural model is based on four critical parameters: collinearity testing using variance inflation factors (VIF) values, hypothesis testing, coefficient determination (R2), and predictive relevance (Q2) (Cohen, 1988).

Firstly, collinearity testing was conducted to ensure that multicollinearity does not affect the results of the structural model. Multicollinearity occurs when independent variables in the model are highly correlated, which can inflate the variance of the coefficient estimates and make the model unstable. To check for multicollinearity, the variance inflation factors (VIF) values were calculated for all latent variables. According to Hair et al. (2012) and Henseler et al. (2009), a VIF value below the threshold of 5 indicates that there is no severe multicollinearity issue. In this study, all VIF values were below this threshold, as shown in Table 5, indicating that multicollinearity was not a concern and the model's estimates are stable and reliable.

**Table-5 Multicollinearity test results**

| Construct | VIF value | Construct | VIF value |
|---|---|---|---|
| **Con** | | **RWD** | |
| Con1 | 3.028 | RWD1 | 2.311 |
| Con2 | 3.980 | RWD2 | 2.044 |
| Con3 | 2.952 | RWD3 | 1.981 |
| **EB** | | **SI** | |
| EB1 | 1.813 | SI1 | 1.844 |
| EB2 | 2.051 | SI2 | 2.198 |
| EB3 | 2.349 | SI3 | 2.450 |
| **FL** | | **T** | |
| FL1 | 2.296 | T1 | 2.508 |
| FL2 | 2.800 | T2 | 2.536 |
| FL3 | 2.607 | T3 | 2.389 |
| **PU** | | **TP** | |
| PU1 | 2.715 | TP1 | 2.809 |
| PU2 | 2.430 | TP2 | 3.375 |
| PU3 | 2.372 | TP3 | 2.815 |
| PU4 | 2.895 | TP4 | 2.517 |
| **PEOU** | | **UI** | |
| PEOU1 | 3.280 | UI1 | 2.255 |
| PEOU2 | 3.320 | UI2 | 2.012 |
| PEOU3 | 2.848 | UI3 | 2.332 |
| PEOU4 | 2.816 | | |
| **FA** | | | |
| FA1 | 2.046 | | |
| FA2 | 2.812 | | |
| FA3 | 3.213 | | |
| FA4 | 3.960 | | |
| FA5 | 3.144 | | |

Secondly, hypothesis testing was performed using the PLS-SEM bootstrapping algorithm. This method involved generating a sample of 5,000 random cases to assess the significance of the relationships between constructs (Hair et al., 2012; Henseler et al., 2009). The bootstrapping process helps in estimating the precision of the PLS-SEM model by providing standard errors and t-statistics, which are used to test the hypotheses.

The results from the hypothesis testing are summarized in Table 6, showing that most of the hypotheses were supported, while a few were not. Specifically, the hypothesis H1 (PU -> FA) was supported with a path coefficient of 0.166, a t-statistic of 2.509, and a p-value of 0.006. The hypothesis H2 (PEOU -> FA) was supported with a path coefficient of 0.545, a t-statistic of 6.584, and a p-value of 0.000. Conversely, the hypothesis H3 (RWD -> PU) was not supported with a path coefficient of 0.002, a t-statistic of 0.024, and a p-value of 0.490.

The hypothesis H4 (EB -> PU) was supported with a path coefficient of 0.227, a t-statistic of 3.238, and a p-value of 0.001. Similarly, the hypothesis H5 (SI -> PU) was supported with a path coefficient of 0.375, a t-statistic of 4.986, and a p-value of 0.000. The hypothesis H6 (UI -> PU) was supported with a path coefficient of 0.145, a t-statistic of 2.071, and a p-value of 0.019.

The hypothesis H7 (CI -> PEOU) was supported with a path coefficient of 0.512, a t-statistic of 7.157, and a p-value of 0.000. The hypothesis H8 (TP -> PEOU) was supported with a path coefficient of 0.368, a t-statistic of

4.802, and a p-value of 0.000. Lastly, the hypothesis H9 (T -> PEOU) was not supported with a path coefficient of 0.076, a t-statistic of 1.372, and a p-value of 0.085.

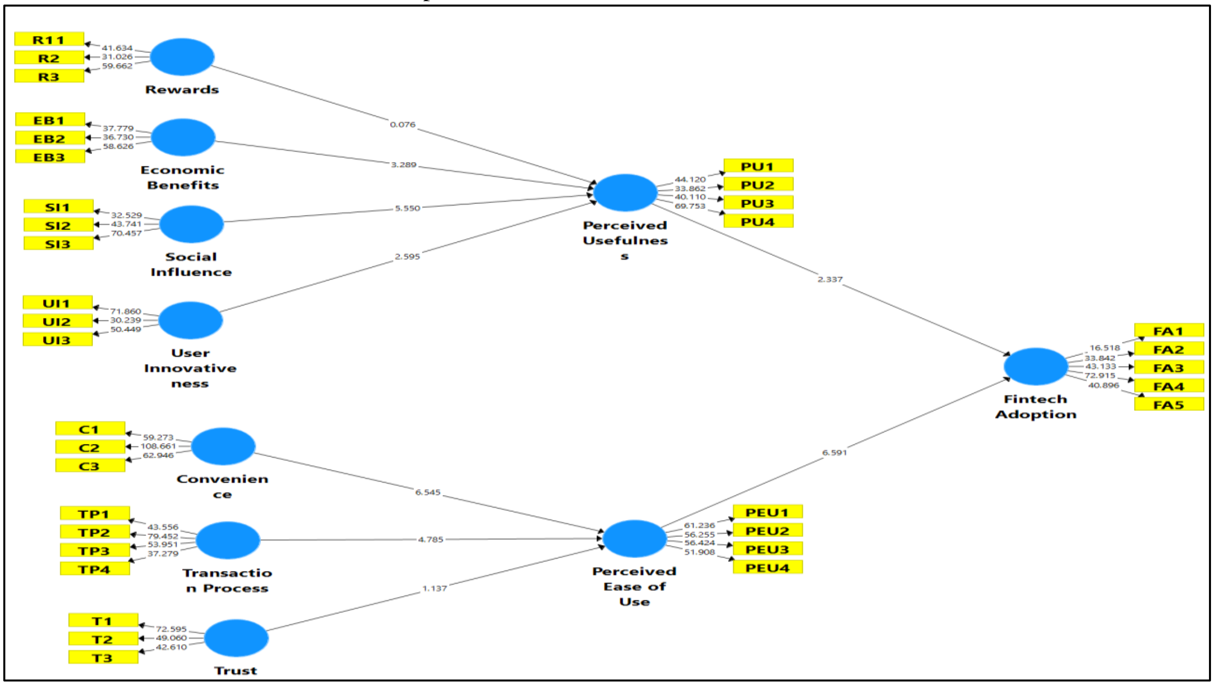


**Figure-2 Results of hypothesis tests**

**Table-6 Hypothesis Testing**

| Hypothesis | Hypothesis Path | Path Coefficient | T-Statistic | p-value | Result |
|---|---|---|---|---|---|
| $H_1$ | PU -> FA | 0.166 | 2.509 | 0.006 | Supported |
| $H_2$ | PEOU -> FA | 0.545 | 6.584 | 0.000 | Supported |
| $H_3$ | RWD -> PU | 0.002 | 0.024 | 0.490 | Not Supported |
| $H_4$ | EB -> PU | 0.227 | 3.238 | 0.001 | Supported |
| $H_5$ | SI -> PU | 0.375 | 4.986 | 0.000 | Supported |
| $H_6$ | UI -> PU | 0.145 | 2.071 | 0.019 | Supported |
| $H_7$ | CI -> PEOU | 0.512 | 7.157 | 0.000 | Supported |
| $H_8$ | TP -> PEOU | 0.368 | 4.802 | 0.000 | Supported |
| $H_9$ | T -> PEOU | 0.076 | 1.372 | 0.085 | Not Supported |

## 4.3Moderating effects

| **Variables** | **Coefficient of determination($R^{2)}$** | **Prediction relevance($Q^{2)}$** |
|---|---|---|
| FinTech Adoption(FA) | 0.513 | 0.513 |
| Perceived Ease of Use(PEOU) | 0.319 | 0.495 |
| Perceived Usefulness | 0.218 | .586 |

Thirdly, the coefficient of determination (R2) was evaluated to determine the model's explanatory power. R2 indicates the proportion of variance in the dependent variable that is predictable from the independent variables. Higher R2 values suggest better explanatory power of the model. In this study, the R2 values for FinTech Adoption (FA), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU) were 0.513, 0.319, and 0.218, respectively. These values indicate a moderate level of explanatory power, which means that the model reasonably explains the variance in the dependent variables (Cohen, 1988).

Finally, predictive relevance (Q2) was assessed using the blindfolding procedure. The Q2 value is obtained through a cross-validated redundancy approach and indicates the model's capability to predict the data points of the endogenous constructs. A Q2 value greater than zero suggests that the model has predictive relevance (Hair et al., 2012). In this study, the Q2 values for FA, PEOU, and PU were all above zero, confirming the model's predictive relevance and its ability to predict the endogenous constructs effectively.

**Table-7 Moderating Role of Financial Literacy**

| Hypothesis | Path Coefficient (Financial Literacy) | t- Value | Decision |
|---|---|---|---|
| PEOU ⇨ FA | 0.000 | 3.792 | Supported |
| PU ⇨ FA | 0.032 | 1.862 | Supported |

The hypothesis testing results for the moderating effects indicate that Financial Literacy significantly influences the relationships between Perceived Ease of Use (PEOU) and FinTech Adoption (FA), as well as Perceived Usefulness (PU) and FinTech Adoption (FA). Specifically, the moderating effect of Financial Literacy on the relationship between PEOU and FA was supported, with a path coefficient of 0.000 and a t-value of 3.792, demonstrating a significant interaction. Similarly, the moderating effect of Financial Literacy on the relationship between PU and FA was also supported, with a path coefficient of 0.032 and a t-value of 1.862. These findings are consistent with previous studies that highlight the importance of Financial Literacy in enhancing technology adoption behaviors (Pousttchi and Schurig, 2004; Lee et al., 2011; Luarn and Lin, 2005).

**4.4 Multi-Group Analysis Using PLS**

For the multi-group analysis, Financial Literacy was taken as the moderating variable, divided into two groups within the constructs of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) using 399 original samples. The findings are summarized in Figures 1. Furthermore, the significance of the differences between the groups was investigated (Henseler et al., 2009; Lowry and Gaskin, 2014). The results are shown in Table 6.

## 5.DISCUSSION

The results of this study provide valuable insights into the relationship between exogenous and endogenous variables in the context of FinTech adoption. Utilizing Structural Equation Modeling (SEM), the analysis confirms both the reliability and validity of the constructs and establishes significant causal relationships among them. These findings align with previous research, particularly the study by Jain and Raman (2021).

The measurement model assessment confirmed the reliability and validity of the constructs. Indicator reliability was demonstrated through outer loadings consistently exceeding the threshold value of 0.7, indicating strong reliability. This finding aligns with the results of Jain and Raman (2021), who also reported high outer loadings, underscoring the robustness of their measurement model. Internal consistency, verified using Cronbach's alpha, showed values surpassing the recommended limit of 0.7, further reinforcing the reliability of the constructs (Hair et al., 2011).

**Convergent validity** was established through composite reliability (CR) and average variance extracted (AVE). The CR values for all constructs exceeded the 0.7 threshold, and the AVE values were above the 0.5 limit, confirming adequate convergent validity (Fornell and Larcker, 1981). This indicates that the indicators of each construct are well-correlated and effectively measure the underlying theoretical concepts. **Discriminant validity** was also confirmed by comparing the square root of the AVE for each construct with the inter-construct correlations, ensuring that each construct is distinct from others (Hair et al., 2012).

The structural model assessment included collinearity testing, hypothesis testing, coefficient of determination ($R^2$), and predictive relevance ($Q^2$). Collinearity testing using VIF values revealed no severe multicollinearity issues, aligning with the guidelines provided by Hair et al. (2012) and Henseler et al. (2009), ensuring stable and reliable model estimates.

Hypothesis testing using the PLS-SEM bootstrapping algorithm provided standard errors and t-statistics to assess the significance of the relationships between constructs. The results indicated that most hypotheses were supported, demonstrating the significant impact of various factors on FinTech adoption. For instance:

- **H1** was supported, with a path coefficient of 0.166 and a p-value of 0.006.
- **H2** was supported, with a path coefficient of 0.545 and a p-value of 0.000.
- **H3** was not supported, with a path coefficient of 0.002 and a p-value of 0.490.
- **H4** was supported, with a path coefficient of 0.227 and a p-value of 0.001.
- **H5** was supported, with a path coefficient of 0.375 and a p-value of 0.000.
- **H6** was supported, with a path coefficient of 0.145 and a p-value of 0.019.
- **H7** was supported, with a path coefficient of 0.512 and a p-value of 0.000.
- **H8** was supported, with a path coefficient of 0.368 and a p-value of 0.000.
- **H9** was not supported, with a path coefficient of 0.076 and a p-value of 0.085.

However, some hypotheses were not supported, such as the relationship between rewards (RWD) and PU. This finding suggests that, while certain factors significantly influence FinTech adoption, others may not have the expected impact.

The coefficient of determination ($R^2$) values for FA, PEOU, and PU indicated a moderate level of explanatory power, suggesting that the model reasonably explains the variance in these dependent variables (Cohen, 1988). Predictive relevance ($Q^2$) was also assessed, with $Q^2$ values above zero for FA, PEOU, and PU, confirming the model's capability to predict the data points of the endogenous constructs (Hair et al., 2012). This highlights the model's effectiveness in capturing the underlying relationships and predicting FinTech adoption behaviors.

The study further explored the moderating effects of financial literacy on the relationships between perceived usefulness, perceived ease of use, and FinTech adoption. The findings indicated that financial literacy significantly moderates these relationships, consistent with previous research highlighting the importance of financial literacy in enhancing technology adoption behaviors (Pousttchi & Schurig, 2004; Lee et al., 2011). Specifically, financial literacy strengthened the positive impact of PEOU and PU on FA, suggesting that individuals with higher financial literacy are more likely to adopt FinTech solutions.

For instance, the hypothesis H10a was supported, with a path coefficient of 0.000 and a t-value of 3.792. Similarly, the hypothesis H10b was supported, with a path coefficient of 0.032 and a t-value of 1.862. These findings align with the results of Jain and Raman (2021), who found that perceived benefits were more influential in FinTech adoption than perceived risks. Both studies emphasize the importance of understanding user perceptions to enhance FinTech adoption. Additionally, the moderating role of financial literacy in this study corroborates the findings of previous research by Lee et al. (2011), which highlighted the significance of financial literacy in technology adoption.

The comprehensive assessment of both the measurement and structural models provides robust support for the proposed hypotheses and highlights the critical factors influencing FinTech adoption. The study findings contribute to the existing literature by confirming the importance of perceived usefulness, ease of use, and financial literacy in driving FinTech adoption, offering valuable insights for policymakers and practitioners aiming to enhance the adoption of digital financial services. The findings of this study affirm the significance of perceived benefits over perceived risks and the vital role of financial literacy in FinTech adoption (Jain & Raman, 2021), providing a robust foundation for future research and practical applications in digital finance.

The adoption of FinTech offers substantial advantages to users, yet some consumers remain hesitant to embrace these services. This study aimed to identify and analyze the factors influencing FinTech adoption using Structural Equation Modeling (SEM). The assessment included measurement and structural models, confirming the reliability and validity of the constructs and establishing significant causal relationships among them.

Perceived usefulness (PU) is a crucial factor in FinTech adoption, as posited by the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh et al., 2003). Our study confirmed that PU positively influences FinTech adoption, indicating that users are more likely to adopt FinTech services if they perceive them as useful (Hair et al., 2014; Chin, 1998). This finding aligns with previous research by Gefen et al. (2003), which highlights the importance of PU in technology adoption. Similarly, perceived ease of use (PEOU) significantly impacts FinTech adoption, supporting the TAM. Users who find FinTech services easy to use are more inclined to adopt them, a result consistent with findings by Venkatesh and Davis (2000) and Gefen et al. (2003). The positive influence of PEOU on adoption was supported with a significant path coefficient, demonstrating that ease of use remains a critical factor in the decision to adopt new technologies (Hair et al., 2011).

Social influence (SI) is another significant determinant of technology adoption, as highlighted by the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Our study demonstrated that SI positively influences PU and subsequently FinTech adoption. This indicates that users are swayed by the opinions of their family, friends, and colleagues, which aligns with findings by Henseler et al. (2009) and Lowry and Gaskin (2014). Economic benefits (EB) also play a critical role in FinTech adoption. Hypothesis H4, which posits that economic benefits positively influence PU, was supported. This aligns with the Diffusion of Innovations theory by Rogers (2003), which states that perceived advantages are critical for adoption. Users are more likely to adopt FinTech if they perceive it to offer economic benefits (Bollen, 1989; Fornell and Larcker, 1981).

User innovativeness (UI) significantly impacts PU, suggesting that users who are inclined to try new technologies are more likely to perceive FinTech as useful and thus adopt it (Rogers, 2003; Agarwal and Prasad, 1999). Convenience (CI) with existing values and experiences is also crucial for adoption. Our study confirmed that CI positively influences PEOU, which is in line with the Innovation Diffusion Theory (Rogers, 2003). When

FinTech services align with users' existing values and experiences, they are perceived as easier to use (Coltman et al., 2008).
Transaction process (TP) positively impacts PEOU, indicating that users find FinTech services easier to use if the transaction process is easily understandable. This finding aligns with previous studies by Agarwal and Prasad (1999) and Henseler et al. (2009). Trust (T) is a critical factor in technology adoption, especially in financial services, although hypothesis H9 was not supported (Gefen et al., 2003; Anderson and Gerbing, 1988). Trust still plays a role in users' perception of ease of use and overall adoption behavior.
Despite hypothesis H3 not being supported, rewards (RWD) can still play a motivational role in user adoption under certain conditions (Lee et al., 2011; Luarn and Lin, 2005). The study also explored the moderating effects of financial literacy on the relationships between PU, PEOU, and FinTech adoption. Financial literacy significantly moderates these relationships, enhancing the positive impacts of PU and PEOU on FinTech adoption. This finding aligns with previous research by Lee et al. (2011) and Pousttchi and Schurig (2004), which highlight the importance of financial literacy in technology adoption. Users with higher financial literacy are better equipped to understand and utilize FinTech services, leading to higher adoption rates (Jain and Raman, 2021).

## 7.CONCLUSION

In conclusion, the comprehensive assessment of the measurement and structural models provides robust support for the proposed hypotheses. The study findings contribute to the existing literature by confirming the importance of perceived usefulness, ease of use, social influence, economic benefits, user innovativeness, convenience, and financial literacy in driving FinTech adoption. These insights offer valuable guidance for policymakers and practitioners aiming to enhance the adoption of digital financial services, providing a robust foundation for future research and practical applications in digital finance (Hair et al., 2012; Fornell & Larcker, 1981).

## 8.Implications

The findings of this study hold significant implications for policymakers, practitioners, and stakeholders in the FinTech industry. Gaining insights into the key factors influencing FinTech adoption can help shape strategies to improve user engagement and satisfaction. Firstly, the positive impact of perceived usefulness (PU) on FinTech adoption underscores the need for FinTech companies to deliver clear and tangible benefits to users (Venkatesh et al., 2003; Davis, 1989). This can be achieved by highlighting how FinTech services improve financial management, save time, and provide accessible financial solutions (Hair et al., 2014). Marketing strategies should emphasize these advantages to enhance users' perceptions of the usefulness of FinTech services.
The significant role of perceived ease of use (PEOU) suggests that FinTech services must be user-friendly and intuitive (Venkatesh & Davis, 2000; Gefen et al., 2003). Developers should prioritize designing interfaces that are easy to navigate and understand, reducing the learning curve for new users (Chin, 1998). Comprehensive tutorials and customer support can further enhance ease of use, making adoption smoother and more appealing (Hair et al., 2011).
Social influence (SI) significantly affects PU and FinTech adoption, indicating that peer recommendations and societal norms play a crucial role in technology acceptance (Venkatesh et al., 2003; Henseler et al., 2009). FinTech companies should leverage social proof through testimonials, reviews, and endorsements from trusted individuals and influencers. Encouraging current users to share positive experiences can create a ripple effect, attracting more users through word-of-mouth (Lowry & Gaskin, 2014).
Economic benefits (EB) positively influence PU, emphasizing the importance of cost-effectiveness in FinTech adoption (Rogers, 2003). Companies should develop pricing models that offer competitive advantages over traditional financial services. Rewards, discounts, and loyalty programs can further incentivize users to choose FinTech solutions, reinforcing their perceived economic benefits (Bollen, 1989; Fornell & Larcker, 1981).
User innovativeness (UI) and convenience (CI) with existing values and experiences are crucial for adoption (Rogers, 2003; Agarwal & Prasad, 1999). FinTech services should be adaptable to diverse user needs and preferences, providing personalized experiences aligned with users' financial habits and goals. Innovations that resonate with users' values can drive higher adoption rates (Coltman et al., 2008).
The study findings on the moderating effects of financial literacy imply that enhancing users' financial knowledge can significantly boost FinTech adoption (Lee et al., 2011; Pousttchi & Schurig, 2004). Policymakers and educational institutions should focus on financial literacy programs that equip individuals with the necessary skills and knowledge to confidently navigate digital financial services (Luarn & Lin, 2005). FinTech companies

can also contribute by providing educational resources and tools that help users understand and make the most of their services (Jain & Raman, 2021).

Trust remains a fundamental factor in the adoption of financial technologies. Although the direct impact of trust was not strongly supported in this study, building and maintaining trust through robust security measures, transparent policies, and reliable customer service is essential (Gefen et al., 2003; Anderson & Gerbing, 1988). Ensuring that users feel secure and that their personal information is protected can alleviate concerns and foster a trusting relationship.

The comprehensive understanding of these factors provides a robust framework for enhancing FinTech adoption. Policymakers should consider these insights when developing regulations and policies to support the growth of the FinTech sector. Practitioners can apply these findings to optimize product development, marketing strategies, and user experience design (Hair et al., 2012; Fornell & Larcker, 1981). By addressing the critical factors identified in this study, the FinTech industry can drive higher adoption rates, ultimately transforming financial services and improving financial inclusion.

## 9.Limitations

This study focuses on the information gathered from 399 respondents and examines how FinTech-based services are adopted in India. Since all respondents are Indian, FinTech usage in other countries may vary, leading to different findings for the same survey. Although the sample of this study is larger, it is based on individual experiences and knowledge. Future studies could investigate groups with varying sample criteria, which may yield different outputs and results. Additionally, since the study only used one theoretical framework—the Technology Adoption Model (TAM)—further research could employ two or more frameworks and focus on specific FinTech-based services.

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