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Impact of Financial Knowledge on Adoption of FinTech Platforms among Academic Professionals: A UTAUT Model Perspective

Mohd Saleem[1], Chanchal Chawla[2]

[1]Research Scholar, TMIMT, Teerthanker Mahaveer University, India, Email: saleem0642@gmail.com
[2]Professor, TMIMT, Teerthanker Mahaveer University, India, Email: chanchal.management@tmu.ac.in

Based on this theoretical framework, the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this study analyses the impact of financial knowledge on the adoption of FinTech Platforms, the new age investment tools among academic professionals. It is intended to demonstrate how FCs, SI, as well as EE and PE shape the adoption intentions of academic professionals, a population generally neglected in investment behavior studies. Data were gathered from academic professionals to examine the relationships between these variables using partial least squares (PLS) structural equation model. The results show that persistence of academic professionals in using new age investment platforms is largely inspired by the factors of financial literacy and the UTAUT model factors like FCs, SI, EE, PE. The findings of this study are relevant for policymakers, financial institutions and platform developers as it identifies the importance of financial knowledge and UTAUT constructs in creating confident and informed adoption of modern investment tools among academics.
Keywords: Financial Knowledge, Investment Behaviour, FinTech, UTAUT Model, Behavioural Intention, Academic Professionals.

1. Introduction

The fast paced development of financial technology (fintech) has instigated a shift in the investment landscape all across globally, making available to the users a set of modernized investment options (Asif et al., 2023) such as Cryptocurrencies, Environmental, Social, and Governance (ESG) Mutual Funds, Infrastructure Investment Trusts (InvITs), Real Estate

Investment Trusts (REITs), and International Equity (Rane et al., 2024). Thanks to these innovations, traditional financial services have been redefined, namely convenience of diversification through expressive digital platforms, access to global markets and socially responsible options (Bittini et al., 2022). Across professional groups, fintech is gaining traction for the way it integrates financial services with technology (Abakah et al., 2023). However, to date, not much has been studied about people using these platforms among academic professionals, a large part of the educated workforce.

Northern Egyptian women are becoming increasingly financially literate, as financial landscapes become increasingly complex and it becomes increasingly difficult for individuals—relative to an historical context—to make informed investment decisions (Bayar et al., 2020). The financial knowledge gives people the capacity to understand, assess, and select the most appropriate investment choice for given amounts of risk, return, and personal financial objectives (Binti Azmi & Ramakrishnan, 2018). Financial knowledge can especially affect whether academic professionals, who have a high disposable income and a great deal of intellectual capital consider adopting fintech platforms (Johan et al., 2021). As new products that are only available with fintech platforms enter the market that require a deep understanding of both finance and technology (Noor et al., 2022), it is important to ask whether financial knowledge is at least as important as technology knowledge in driving adoption for this group (Sreenu, 2024).

While fintech platforms come with their advantages there is a gap in adoption rates among some groups of demographic especially among academic professionals. There may be several factors that could have prevented people from using these digital financial services and products; one could be not being familiar with digital financial services (Koskelainen et al., 2023); one is a fear of safeguarding their data or one doesn't really understand what are they investing in (Katiyar, 2020). Furthermore, despite the wide use of the Unified Theory of Acceptance and Use of Technology (UTAUT) model to study technology adoption, very few studies have studied its application with fintech investment platforms focused on how financial knowledge affects adoption behavior (Kurniasari et al., 2022). This gap points to the importance of studying how the use of fintech platforms among academic professionals is affected by the use of fintech platforms, given financial knowledge and technology acceptance factors.

This study aims to see how financial knowledge affects the adoption of fintech investment platforms among academic professionals using the UTAUT model. It narrows the focus to academic professionals since this group has distinctive characteristics that it confronts sharply with barriers when a fintech solution is proposed to it. On a more specific note, the study will examine how much a person's financial knowledge influences the adoption of fintech platforms and how effectively these constructs—Usefulness Perceptions (Performance Expectancy, Effort Expectancy), Social Influence, and Facilitating Conditions—function in predicting such adoption (Abdullah et al., 2018).

In both theoretical and practical terms, this research is important. It is theoretically important to the existing literature on fintech adoption by augmenting the UTAUT model with the dimension of financial knowledge. On one level, the findings may shed light on how financial realities affect academic professionals' financial literacy and investment behavior, which could be useful to fintech companies, financial educators and policy makers interested in improving financial literacy and responsible investment behaviors. Knowing how financial knowledge affects FinTech's adoption helps broaden the educational institutional and organisations of fintech provision.

The study is guided by the following research questions:

- How much does financial knowledge matter when it comes to academic professional's use of fintech investment platforms?
- What makes academic professionals want to use fintech platforms?
- How much do these UTAUT factors interact with financial knowledge to affect the adoption of FinTech's adoption of fintech investment platforms among academic professionals?
- How do UTAUT constructs (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) influence the adoption of fintech platforms by academic professionals?
- To what extent does financial knowledge interact with these UTAUT factors in influencing fintech adoption?

This part sets up this work by positioning the consideration of financial knowledge, and creating a prelude for a more thorough UTAUT driven investigation.

2. Review of Literature

Advances in technology, changes in regulatory frameworks, and changes in investors' preferences are the drivers of exponents expansion in the fintech sector (Abraham & Chengalur-Smith, 2010). With access to digital services over the Internet (such as Digital Banks), fintech platforms are revolutionizing traditional finance through new investment opportunities and financial inclusion (Alkhowaiter, 2020). Recently, fintech platforms have empowered democratization of access to investment by simplifying processes, lowering entry barriers, and providing advanced tools like robo advice, predictive analytics and real time trading capabilities (Feyen et al., 2021). Yet, despite widespread adoption of these platforms, there is a blatant gap in demographic adoption, featuring the adoption of these platforms varying significantly between demographic groups (Desai, 2022).

They also happen to have an interesting profile: many of them are academic professionals with an education that might predispose them to use these platforms. While this group also has its own unique challenges to fintech adoption to include balancing complex academic responsibility, little time for investment research and sometimes conservative financial preferences, these can also be barriers (H.-H. Chang et al., 2024). Although these barriers exist, research reinforces growing interest for fintech platforms amongst university professionals due to demand for low cost and diversified investment options (Alshamrani et al., 2019).

Among the dizzying array of fintech platforms, there are some 'new-age' investment options which have gained prominence. These options include:

- Cryptocurrencies: With several cryptocurrencies such as Bitcoin and Ethereum having attracted significant interest from the digital assets space recently for both their decentralized structure and potential for high returns, it makes sense that investing in these cryptos is high on anyone's list. While their volatility and regulatory issues make them risky to investors, especially those with little experience of market dynamics (Y. Chen & Yu, 2024).

- ESG Mutual Funds: Socially conscious investors like the investments that are focused in environmental, social and governance (ESG) criteria. As academic professionals frequently relate to ESG funds through values of social responsibility, ESG funds are perceived as the way to achieve financial returns while promoting ethical practices (Becker et al., 2022).

- InvITs and REITs: If you want to invest in the infrastructure and real estate assets, Infrastructure Investment Trusts (InvITs) and Real Estate Investment Trusts (REITs) are available as a stock market product. Investors seeking low risk, long term returns like these options: have potential to provide steady income, tax benefits and portfolio diversification (Bohra et al., 2024).

- International Equity: Today, Fintech platforms allow investors to tap into global markets thus diversifying their portfolio across geographies. This option is attractive to academic professionals who can have a taste for high growth markets located in their home country as a hedge against local economic fluctuations (Longin & Solnik, 2001).

Investors looking for diversification, social impact, or exposure to innovative financial products really like these new age investment options. But these investments also come with complexity and risk and need a certain level of financial knowledge to make them work (Obamuyi, 2013).

Investment behavior is greatly determined by financial knowledge, whether influencing the ability of individuals to make educated decisions, take risks, reach financial goals (Kartini & NAHDA, 2021). Research has shown that financially informed individuals are more likely to diversify their portfolios, find innovative investment opportunities, and, better yet, manage risk (Lusardi & Mitchell, 2011). In the field of fintech, it has been shown that having knowledge of finance is essential because users are able to understand the risks and the rewards connected with varying investment options starting from typically stocks and moving further into predominantly virtual assets such as cryptocurrencies (Sultana et al., 2023).

Finances are something for academic professionals to have knowledge about and it influences the perception and adoption of fintech platforms (Kurniasari et al., 2022). Despite being generally well educated, this demographic does not necessarily need the specialized financial knowledge necessary to evaluate FinTech options effectively (Xie et al., 2008). Fintech studies acknowledge that people are not always comfortable to navigating financials but targeted financial literacy can raise the confidence on making investment decisions thus improving individuals' chances of subscribing to fintech platforms (Sharma et al., 2024). Given how advanced and accessible some of them are to people of all backgrounds, it becomes crucial to understand the perimeter of the relationship between financial knowledge and fintech adoption.

Taking into account the topic of technology adoption, the Unified Theory of Acceptance and Use of Technology (UTAUT) model offers a framework by which to understand and assess user perception and use of fintech platforms (Yohanes et al., 2020). The UTAUT model, developed by Venkatesh et al. (2003), is based on four primary constructs:

- Performance Expectancy: Lastly, it relates to the belief of the individual believing that usage of a technology will improve his/her efficiency. In the case of fintech platforms, the performance expectancy is understood as the perceived change in investment returns or financial management efficiency. The direction of previous studies has shown that users are less willing to on fintech platforms when they expect to make higher returns, while users are more willing to on fintech platforms if they expect to have streamlined investment processes (W.-L. Chang et al., 2024).

- Effort Expectancy: The effort expectancy is defined as the ease of use of a technology. The main aim of fintech platforms is to make financial transaction easier and to easier access investment for a wider range of audience. Yet, for academic professionals used to an academic daily routine, they are concerned with perceived ease of use. According to research, users are more engaged when fintech platforms are easy to use (Bhatnagar et al., 2023).

- Social Influence: The more people feel that important (other) people think they should use a particular technology, the greater is the social influence. Social influence is especially powerful driver of fintech in academic environments, as peer influence and professional networks vastly impact adoption. Authors have shown that social influence is most efficient in contexts people value trust and reputation, as is the case with investment decisions (Bozan et al., 2016).

- Facilitating Conditions: This construct views resources and support available to those who adopt and use a technology. In the Fintech context, which may involve things like access to digital infrastructure, educational resources on investment and customer support, facilitating conditions would be: Support structures such as online tutorials, webinars, access to research about fintech investments can make a big difference in terms of the willingness of academic professionals to adopt such platforms (L. Chen et al., 2023).

With the help of the UTAUT model we have a robust framework to examine the interplay of financial knowledge and technology acceptance to explain adoption of fintech platforms. The impact of each construct on their engagement with new age fintech platforms is examined to understand the various complex factors that have an impact on academic professionals' interest in the participation with new age fintech platforms.

3. Research Methods

In this study, the dependent variable (DV) is termed to be the behavior of investing in fintech and it is investigated using a quantitative research approach through factors that influence the use of fintech among academic professionals of India (Lee et al., 2010). The following table contains the list of iv (financial literacy, facilitating conditions (FCs), social influence (SI), performance expectancy (PE), and effort expectancy (EE) as independent variables. Two sections of a structured, self-administered online survey were targeted to individuals aged 24 or above, and data were collected. The first section conducted demographic data, including age, gender, education level and professional background whereas the second section collected perceptions on key variables including financial literacy, perceived risk, facilitating condition and social influence. They were measured on a 5 points Likert scale (Nemoto & Beglar, 2014) from “Strongly agree” to “Strongly disagree” to get nuanced insights of the participant’s views about investment platforms.

The data was collected through the online forms over a four months’ period (March – June 2024). This study set out to gain insight on how academic professionals are influenced by what they know about education, their financial literacy and familiarity in technology with the perception of investment platforms. Inclusivity without bias for gender or age or income was ensured through distribution of survey invitations to persons meeting the academic profile, leading to a representative sample. Of 411 total responses, 354 were deemed valid, offering the complete picture of how this educated demographic would approach investment platforms. Consequently, the structured survey methodology provides a rigorous analysis of the relationships between financial knowledge and the UTAUT model constructs for the development of the hypotheses for this research.

Individuals’ belief in having resources to use a technology is called Facilitating Conditions (FCs). Previous studies prove inconclusive on the effect of FCs on technology adoption (Arias-Oliva et al., 2019) (Duarte & Pinho, 2019). This study hypothesizes that

H1: FCs positively influences the intent to use FinTech Platforms among academic professionals.

Effort Expectancy (EE) measures how easy users perceive the technology to be. Research suggests a positive link between ease of use and technology adoption (Dong, 2019) (Zhou et al., 2019). Thus,

H2: EE positively influences the intent to use FinTech Platforms among academic professionals.

Performance Expectancy (PE), the degree to which technology helps users achieve tasks, is a key UTAUT variable. Studies suggest PE boosts the intention to use services, including cryptocurrencies (Aronson & Carlsmith, 1962). Hence,

H3: PE positively influences intent to use FinTech Platforms among academic professionals.

Social Influence (SI), based on Kelman’s theory, reflects how others' opinions shape technology adoption. Studies confirm SI significantly affects intentions to use crowdfunding and mobile banking (Bozan et al., 2016). Therefore,

H4: SI positively influences intent to use FinTech Platforms among academic professionals.

Financial literacy, defined as understanding financial concepts and making informed decisions, is critical in financial behavior. Studies show that higher financial literacy increases participation in financial markets and investments. Hence, H5: Financial literacy positively influences intent to use FinTech Platforms among academic professionals.

4. Data Analysis & Descriptions

With 354 respondents, the demographic profile provides valuable description in terms of gender, age, education level, investment experience, academic profession, etc. This analysis assists in the understanding the characteristics of the sample population and posits a framework for understanding the investment behavior and attitude of the sample population. The sample is heavily skewed towards males, who make up 70.90% of the total (251) sample, by gender. 29.10 % (103 individuals) are responding as females. This large difference strongly suggests, if gender differences are at play in such things as investment preference or behavior, that males dominated the sample population.

Table 1: Demographic Profile of Respondents

Demographics	Profiles	N: 354	
		f	%
Gender	Male	251	70.90
	Female	103	29.10
Age	24-34	248	70.06
	35-45	57	16.10
	46-56	33	9.32
	56+	16	4.52
Education	Graduate	92	25.99
	Post Grad.	188	53.11
	Ph.D.	65	18.36
	Professional Degree	9	2.54
Investment Experience	Less than 2 Years	87	24.58
	2-4 Years	148	41.81
	4-6 Years	85	24.01
	6 Years+	34	9.60
Academic Profession	Teaching	265	74.86
	Non-Teaching	89	25.14

Age distribution shows a younger response with 70.06% (248 respondents) belonging to 24-34 age group. The 35-45 age group is next with 16.10% (57) and followed by the 46-56 age group at 9.32% (33). Only 4.52 per cent (16 respondents) are from the youngest group, 56 and older. The fact that so many of the respondents in this sample are younger respondents means that the sample might be capturing perspectives that would be fairly typical of individuals in early to mid-careening. This group is full of rather intelligent people, as education levels are high. The postgraduate has made up over half of the respondents as 53.11% (188 people) holding a postgraduate degree, while 25.99% (92 people) are graduates. Moreover, 18.36 per cent (65 respondents) have a Ph.D. and 2.54 per cent (9 individuals) have a professional degree. The sample is well educated, a high level of educational attainment, and this may be correlated with being financially literate and aware of investment opportunities that may then impact investment decisions. In terms of investment experience, respondents are most common at 41.81% (148 people) with 2-4 years' experience. Furthermore, 24.58 percent respondents (87 respondents) have less than 2 years of experience, which also shows a high amount of novice investors. About 24.01% (85 persons) have 4-6 years of experience, 9.60% (34 respondents) have over 6 years of experience. The distribution implies the range of investment experience, as majority lie in the early stages of investment path.

The academic profession category with finally shows that a good percentage of respondents is found in teaching roles with 74.86 % (265 respondents) and 25.14 % (89 respondents) respectively in other professions. The survey's strong representation of teaching professionals may also have led respondents to formulate their views on financial and investment issues in an academic setting (Table 1).

Overall, the sample consists of young, male, highly educated teaching professionals of varying levels of investment experience. An important part of interpreting the study's findings is placed contextually through this demographic profile, particularly with respect to academic professionals, most of whom are early or mid-career and, consequently, hold limited wealth and small pools of investible assets.

Table 2: Constructs & its Descriptions

Constructs	Variables	Questions of Concerns	Source
Performance Expectancy	PE1	Using FinTech Platforms will intensify prospects to attain financial goals for me	Adapted from the UTAUT 2 Scale (Venkatesh et al., 2012)
	PE2	FinTech Platforms will support me attain my financial goals more swiftly	
	PE3	Using FinTech Platforms will intensify my standard of living	
Effort Expectancy	EE1	Easy to learn for me to practice FinTech Platforms	Adapted from the UTAUT 2 Scale (Venkatesh et al., 2012)
	EE2	Using FinTech Platforms will be clear and logical for me	
	EE3	It is easy for me to use FinTech Platforms	
	EE4	It is easy for me to become an expert in the use of FinTech Platforms	
Social Influence	SI1	The less-important people to me will contemplate that I must practice FinTech Platforms	Adapted from the UTAUT 2 Scale (Venkatesh et al., 2012)
	SI2	The influencer for me will contemplate that I must use FinTech Platforms	
	SI3	Persons whose thoughts I value would like me to use FinTech Platforms	
Facilitating conditions	FC1	I have the essential means to use FinTech Platforms	Adapted from the UTAUT 2 Scale (Venkatesh et al., 2012)
	FC2	I have the required familiarity to practice FinTech Platforms	
	FC3	FinTech Platforms are well-suited with other tools that I use	
	FC4	I can acquire support if I have difficulty by means of FinTech Platforms	
Financial Literacy	FL1	Level of understanding about FinTech Platforms	Based on Hastings et al. (2013)
	FL2	Investing through FinTech Platforms would be difficult for me due to lack of understanding of concept	
	FL3	Have you ever helped someone to invest through FinTech Platforms by making them aware about the basics of it?	
	FL4	Understanding of FinTech Platforms is helpful in investing	
Investment Behaviour	IB1	I intend to use FinTech Platforms	TAM2 scale (Venkatesh and Davis, 2000)
	IB2	I predict that I will use FinTech Platforms	

a. Assessment of Structural Model

The Measurement Model Results were analyzed using the Smart PLS 3.0 according to suggestions of (Ringle et al., 2020), they claimed that Partial Least Squares Structural Equation Modeling (PLS-SEM) is a good tool to use in such permutation. CR, FL, DV and AVE were used to evaluate the measurement model. Table 3 summarize the results. Investment behavior in cryptocurrency was analyzed in terms of perceived risk, financial literacy, social factors and facilitating conditions. Included in Table 5 are all factor loadings, which are all greater than 0.50, and thus comply with convergent validity (CV) as per Hair (2010).

Table 3: Validity & Reliability of Constructs				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Facilitating Condition	0.926	0.913	0.918	0.676
Performance Expectancy	0.918	0.928	0.926	0.745
Effort Expectancy	0.975	0.948	0.946	0.565
Social Influence	0.91	0.911	0.901	0.675
Financial Literacy	0.932	0.923	0.915	0.743

Similarly, all of the CR and Cronbach's alpha values for all the variables exceeded the minimum requirements of 0.70 and 0.95 respectively (Jr. et al., 2017) which confirmed strong internal consistency (Table 3). Assessments of CV were made using FLs, Cronbach's Alpha, AVE, and CR, and CV is considered accepted if the AVE is 0.5 or greater (Chin, 1998).

As shown in Table 2, all of constructs in this study exceeded or met the AVE and CR thresholds. Tables 4-5-6 present the results confirming discriminant validity (DV) using Fornell Larcker, cross loading and the Heterotrait – Monotrait ratio of correlations (HTMT).

Table 4: Discriminant Validity (Fornell-Larcker Criterion)						
	Facilitating Condition	Investment Behaviour	Performance Expectancy	Effort Expectancy	Social Influence	Financial Literacy
Facilitating Condition	0.819					
Investment Behaviour	0.763	0.862				
Performance Expectancy	0.741	0.868	0.741			
Effort Expectancy	0.762	0.854	0.862	0.809		
Social Influence	0.733	0.873	0.911	0.831	0.861	
Financial Literacy	0.811	0.881	0.909	0.877	0.921	0.857

The Fornell-Larcker (Table 4) criteria associated with DV indicate that each construct is more closely linked to its construct indicators than to the indicators of other constructs. The cross loading criterion states that if an indicator loading on one construct is larger than its correlation with other constructs. DV is also further supported by the HTMT, which should be less than 0.9. In this study all DV criteria were met.

To assess fit of the structural model, the robust bootstrapping approach with Smart PLS 3.0 (5000 resamples) was used to test significance of path coefficients. Following guidelines from (Shmueli et al., 2016) from the structural model assessment, path coefficients, coefficient of determination (R^2), and effect size [f^2] were examined. The statistical significance of sub construct weights and path coefficients was assessed using a bootstrapping technique, Table 7, which displays R^2 values for dependent and independent variables. The coefficient of determination, R^2, thus gives an indication of the fraction of variance in dependent variable described by the independent variables in the model, a measure to predict accuracy.

Table 5: Cross loadings						
	Facilitating Condition	Investment Behaviour	Performance Expectancy	Effort Expectancy	Social Influence	Financial Literacy
FC1	0.611	0.665	0.672	0.663	0.855	0.657
FC2	0.574	0.662	0.627	0.621	0.816	0.591
FC3	0.663	0.712	0.631	0.695	0.859	0.64
FC4	0.563	0.601	0.603	0.554	0.763	0.542
PE1	0.632	0.702	0.62	0.631	0.837	0.623
PE2	0.673	0.721	0.664	0.691	0.571	0.782

PE3	0.655	0.677	0.651	0.642	0.543	0.743
EE1	0.671	0.689	0.631	0.641	0.551	0.733
EE2	0.642	0.661	0.616	0.584	0.564	0.696
EE3	0.689	0.681	0.623	0.635	0.533	0.722
EE4	0.799	0.752	0.885	0.747	0.691	0.746
S11	0.752	0.754	0.852	0.735	0.603	0.762
S12	0.763	0.785	0.888	0.776	0.693	0.761
S13	0.764	0.783	0.862	0.712	0.681	0.74
FL1	0.733	0.765	0.849	0.745	0.639	0.736
FL2	0.699	0.786	0.704	0.66	0.645	0.785
FL3	0.689	0.703	0.64	0.702	0.622	0.773
FL4	0.682	0.725	0.668	0.645	0.619	0.756
L1	0.744	0.713	0.642	0.661	0.589	0.75
L2	0.714	0.73	0.675	0.623	0.6	0.748

The explanatory power of each predictor is given in Table 7 with corresponding adjusted R^2 values. The r-square values near 0.75 is strong, 0.50 is moderate, and 0.26 is weak (Henseler et al., 2009) (Jr. et al., 2017).

Table 6: Heterotrait-Monotrait Ratio (HTMT)

	Facilitating Condition	Investment Behaviour	Performance Expectancy	Effort Expectancy	Social Influence	Financial Literacy
Facilitating Condition						
Investment Behaviour	0.763					
Performance Expectancy	0.737	0.867				
Effort Expectancy	0.761	0.851	0.869			
Social Influence	0.734	0.871	0.81	0.823		
Financial literacy	0.801	0.88	0.81	0.863	0.821	

An effect size (f^2) was calculated by observing changes in R^2 as exogenous variables were dropped from model. F^2 effect sizes according to (Cohen, 2013) are considered weak (≥0.02), moderate (≥0.13) and strong (≥0.35) (Table 8).

Table 7: R-Square

	R-Square	R-square adjusted
Investment Behaviour	0.061	0.04

Table 8: f-Square

	Investment Behaviour	Effect Size
Facilitating Condition	0.043	Moderate
Performance Expectancy	0.103	Moderate
Effort Expectancy	0.369	strong
Social Influence	0.242	strong
Financial Literacy	1.105	strong

Tables 9 presents that the effect sizes of facilitating conditions, Performance expectancy, Effort expectancy, social influence and financial literacy on investment behavior are in a moderate to strong range. In a weak f^2 value is still meaningful because it also impacts the dependent variable, as (Chin, 1998) indicate.

Table 9: Structural Model (Mean, ST DEV, T-value, P Value)

	Novel Sample (O)	Sample Mean (M)	Standard Dev. (ST.DEV.)	T statistics (|O/STDEV|)	P Values
Facilitating Condition -> Investment Behaviour	0.688	0.669	0.049	13.762	0.011
Effort Expectancy -> Investment Behaviour	0.408	0.401	0.146	2.108	0.005
Performance Expectancy -> Investment Behaviour	0.292	0.3	0.124	1.989	0.019
Social Influence -> Investment Behaviour	0.766	0.767	0.044	17.031	0.007
Financial Literacy -> Investment Behaviour	0.512	0.524	0.144	3.981	0.005

The main objective of the study was to examine the influence of a number of factors on the intent to use cryptocurrency using five direct hypotheses (H1 – H5).

Table 10: Results of Hypothesis

Hypothesis	Path Relations	T statistics (|O/STDEV|)	P Value	Results
H1	Facilitating Condition -> Investment Behaviour	13.762	0.011	Accepted
H2	Effort Expectancy -> Investment Behaviour	2.108	0.005	Accepted
H3	Performance Expectancy -> Investment Behaviour	1.989	0.019	Accepted
H4	Social Influence -> Investment Behaviour	17.031	0.007	Accepted
H5	Financial Literacy -> Investment Behaviour	3.981	0.005	Accepted

Positively influencing the cryptocurrency usage intent is each hypothesis proposed each hypothesis each proposes the effect of facilitating conditions (FCs), effort expectancy (EE), performance expectancy (PE), social influence (SI), and financial literacy. In Table 10, all five hypotheses (H1 to H5) were supported, and t values are larger than 1.96. Following the methodology suggested by (Jr. et al., 2017) and (Hayes & Preacher, 2013), we applied PLS-SEM to analyze the effects in which bootstrapping was used. The t values were computed in Smart PLS 3.0 using 5000 resamples.

5. Theoretical and Practical Implications

Various aspects about the new age investment platforms have been studied in the recent studies like the perception of users and challenges, possibilities of investment in digital finance (Chuen & Deng, 2017), factors influencing user behaviour, innovative applications of tech in fintech (M. Hamakhan, 2020), and elements encouraging investment on these platforms. There is a gap in the literature on those specific determinants which can influence investor adoption behavior among Indian academic investors in emerging investment platforms. To fill this gap, this study employs the Smart PLS SEM model to explore behavioral intent of adopting these platforms.

This research aims to identify critical factors that impact investor, platform manager and customer acceptance of new age investment platforms. The literature available suggest that risk perception and financial knowledge are important in making a decision of investing in digital assets. Secondly, research indicates that financial literacy has a great effect in the way investors evaluate, and reduce risk, in these virtual markets (Park and Irwin, 2020). This present study confirms this by showing that the Unified theory of acceptance and use of technology (UTAUT) model variables alongside financial literacy explains investment behavior (Table 10). In related work, previous researchers have indicated that social influence (SI) appears not to directly affect behavior within digital finance (Dong, 2019) (Bozan et al., 2016). For example, studies on facilitating conditions (FCs) provide too scant direct influence over investment behavior in these places (Djalilov & Ülkü, 2021). These insights align with our findings: Factors, such as social influence and facilitating conditions, do not directly drive adoption for digital investment platforms, but instead they are secondary drivers of digital investment platforms adoption.

Further investigation is made into the degree to which FCs, EE, PE, SI, and financial literacy impact investment behavior on new age platforms. Previous research offers strong supporting evidence of a relation between FCs and investment behavior (Djalilov & Ülkü, 2021). We confirm these findings and show that UTAUT model variables, as a combination, impact investment behavior, with financial literacy positively and statistically significantly. In adopting this new age investment platform, these findings highlight the role of financial literates and UTAUT variables in the determination of investor engagement and behavioral intention which enable a better understanding of how investors manoeuvre through the risk and opportunity of the modern digital investments.

6. Findings, Limitations and Recommendations

Several limitations in this study should be mentioned to explain its results. Secondly, the sample size was small (efforts were based on 354 retail investors in India). However, while the results on this limited sample size may or may not generalize to a broader investor population, the narrow demographic focus does not reflect the diversity of perspectives that could come from a more diverse group of investors. Future research should account for larger sample sizes of institutional investors as well as multiple countries, in order to make our study's applicability more attainable. This would enable cross cultural comparisons and illumination of differences in the behavioral of investment across diverse financial markets.

Furthermore, the study shed light on a limited but important set of factors that determine investor behavior. Future research can be further extended to alternative variables, including psychological traits (e.g. risk tolerance), technology familiarity, and external conditions (e.g., regulatory change, economic conditions). The inclusion of these other factors would just add to the complexities of the investor decision making. In addition, this study might not fully reflect actual investment behavior. For future research this could be a longitudinal approach to see how an initial intention becomes a real behavior over time as markets and technologies change. Such a treatment would provide valuable insight into how investors come to grips with a dynamic financial environment, and benefit policymakers and professional financial advisors.

Overall, although the results of this study make an important contribution to understanding investor behavior among retail investors in India, there are some opportunities to add variation to the sample, include additional variables, and use a longitudinal approach to explore richer, less stereotypical patterns. The intention of these recommendations is to advance the relevance and depth of future research on investment behavior in varied and international contexts.

7. Conclusion

Through the analysis of the key factors affecting an investor decision for cryptocurrency investment, this study introduces valuable insights into consumer behavior. The use of a partial least squares (PLS) model investigates the relationship between financial literacy, facilitating conditions (FCs), social influence (SI), and perceived risk, and the investment behaviors of retail investors in India. This shows that these factors are pretty important in creating Indian investors' intentions on cryptocurrency investment and some of UTAUT model factor variables like effort expectancy (EE) and performance expectancy (PE) have a stronger positive impact on their behavior on cryptocurrency investment. Taken together, the results imply that the integration of financial literacy, FCs, SI, EE and PE can explain the adoption of cryptocurrency among the retail traders. This finding draws attention to the fact that these factors should be addressed when enhancing the understanding of investors' behavior, especially in the case of emerging markets such as cryptocurrency. Empirical evidence in these areas can enhance understanding which will help to support informed decision making for investors among policymakers, and financial institutions and educators to contribute to a more sustainably and inclusive investment environment.

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