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Influence of Digital Financial Education and Peer Recommendations on Mutual Fund Purchase Intention: The Mediating Role of Perceived Usefulness

F. Josephine Lenta, J. Kumar*

Department of Commerce, Faculty of Science and Humanities, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, Tamil Nadu, India. *Email: kumarj2@srmist.edu.in

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ABSTRACT

The present study investigates the determinants of investment intention of retail investors in mutual funds using online modes. Peers' recommendation (PR) direct effects on mutual fund buying intention and digital financial education (DFE) direct effects are investigated, along with the mediating role of perceived usefulness (PU). Data was collected from 340 respondents and SmartPLS 4's partial least squares structural equation modelling (PLS SEM) was used for the analysis. The results show that both PRs and DFE significantly increase purchase intent, both directly and indirectly through PU. According to the study, PU plays a cognitive mediating role in converting external information into investment intentions. These observations complement the literature on digital adoption and behavioural finance, while also offering practical implications for FinTech platforms and policymakers aiming to promote mutual fund adoption and financial literacy among emerging investors.

Keywords: Digital Financial Education, Peer Recommendations, Perceived Usefulness, Mutual Fund Purchase Intention, Pls-Sem, Fintech Adoption
JEL Classifications: G41, G51, D83

1. INTRODUCTION

The Indian mutual fund industry has expanded numerous times in the past 10 years, with the development of digital technology as well as the rise in the usage of the internet. Industry average assets under management have grown from 14 trillion rupees to over 32 trillion rupees in just 5 years, based mostly on digital growth (AMFI, 2022). According to the argument made by Deb et al. (2025), the growth has been driven by increased usage of technology-based customer relationship management (CRM) solutions. These innovations have changed how investors interact with investment funds so that procedures like KYC, investments, redemptions, and portfolio monitoring can now be accessed via websites and mobile applications.

Various FinTech companies and banks such as HDFC, ICICI, and SBI have adopted AI-based CRM software. This software provides customers with customized investment recommendations, predictive analytics, and round-the-clock service without requiring human advisors to intervene (Ali and Alfayez, 2024; Kumar et al., 2023). These platforms increase retail investor participation by inducing loyalty, improving satisfaction, and building trust (Tajvidi et al., 2021; Dubey and Sangle, 2018). SIPs of ₹100-₹500 are now prevalent in semi-urban and rural markets, where the reach of mutual funds is now being expanded beyond the urban markets through digital empowerment. Investment accessibility is democratized by ease of use of internet-based KYC ecosystems and mobile banking (Nugraha et al., 2022). Evidence shows that mutual fund investors are increasingly using digital platforms instead of seeking advice from others. Convenience, ease and

trust based on data are the driving factors for this change in investment behavior (Kim and Kim, 2025; Kasemharuethaisuk and Samanchuen, 2023).

Higher financial awareness has a very strong effect on investment decisions and investor confidence, particularly on high-risk products like mutual funds (Chen et al., 2023; Vörös et al., 2021; Lee et al., 2019). Mutual fund knowledge—risk-return tradeoffs and fee structures—are more cognizant of investing and staying invested, particularly mutual funds (Nilsson et al., 2024; Kaur, 2018). The increased investment in online presence, particularly in and post-COVID-19, has made real-time information transfer easier and allowed retail investors to access mutual fund information easily through apps, influencer posts, and online forums (Gao et al., 2025; Mou et al., 2024). Self-efficacy—believing in one's ability to make investments—is also among the strongest predictors of positive investment fund attitude. Confidence-building educational information is therefore likely to strengthen investment confidence and attitudes (Che Hassan et al., 2024; Suresh, 2024).

Social influence is also an important driver of financial behavior and an important factor in the decision to buy investment funds. Peer word-of-mouth, however, is a powerful driver to influence ambiguity and investment decision attitudes (Rohden and Espartel, 2024). In the current digital age, peer influence is further facilitated by media like WhatsApp groups, Reddit forums, and social media, where PRs and mutual fund performance are extensively discussed. Peer-provided advice is also found to be more recognizable and credible compared to institutional advice, thus increasing investors' confidence and action intention. This corroborates earlier studies that show that consumers take familiar social groups when making financial choices (Hafit et al., 2020; Mishra et al., 2023).

TAM also identifies PU as a principal determinant of technology adoption behavioral intention (Davis, 1989). In mutual fund contexts, use of peer advice or online learning is PU's effectiveness in describing risks, returns, and rewards from investments. Investors who believe that digital aids are helpful use them, studies have found (Mishra et al., 2023). Investors who believe that mobile apps or online guides are helpful in describing finance concepts, say, are more investment-focused. PU serves as a mediator between external stimuli (e.g., peer comment or learning) and internal decision-making (Kim and Lee, 2008; Teo et al., 2015; Mishra et al., 2023).

DFE increases decision-making capacity and financial literacy (Mishra et al., 2024; Kumar et al., 2023). Online learning platforms are revolutionizing the way young investors approach mutual funds through YouTube channels, gamified learning, social media explainers, and mobile applications. When these vehicles are combined with PRs, they can yield greater clarity, confidence, and motivation to invest. PU of this composite information is pivotal: It decreases perceived risk (Nicolescu and Tudorache, 2021) and provides confidence in one's financial capability (Furrebøe and Nyhus, 2022). Therefore, the adoption of mutual funds is not so much a process of influence or knowledge, but rather the extent to which users find these online resources useful in their decision-making process (Kasemharuethaisuk and Samanchuen, 2023).

Even though the role of social influence and digital platforms on financial behavior continues to grow, research shows that there is a knowledge gap on how DFE and word-of-mouth individually and jointly influence the purchase intention—for investment funds—especially through the mediating effect of PU. Most existing studies focus either on investor behavior (Chavali and Rosario, 2019), CRM technology (Deb et al., 2025), or attitude and awareness (Kaur, 2018; Goyal and Kumar, 2021), but not on the combination of variables in a model. This research attempts to close this research gap by empirically examining how DFE and PRs individually and jointly influence PU and thus purchase intention. Based on TAM and behavioral finance theories, this study aims to provide FinTech companies, policymakers, and investment educators with actionable insights to promote informed financial inclusion.

2. REVIEW OF LITERATURE

Various studies on mutual fund purchase behavior have mostly evolved along two overarching thematic streams. One is on social and behavioral determinants, with an emphasis on the impact of social norms, herding, and peer advice. The other is on financial literacy and investor education in the digital era, with a focus on the influence of greater access to financial information, particularly through digital channels, on investment behavior. Previous studies have mostly analysed objective determinants such as fund performance, risk-return trade-offs, and investor characteristics. Current studies, however, look at how technology-based financial education and social influences affect people's decisions to invest in mutual funds (Idrees and Ullah, 2024; Mishra et al., 2023; Deb et al., 2023; You et al., 2023).

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There are unique features to the understanding of how people embrace mutual fund products in technology-enabled environments. Unlike conventional products, financial products involve inherent risk, complexity, and long-term implications. The

extensive use of technology-enabled financial platforms changed the manner in which investors make choices on mutual fund products. At the same time, online learning platforms and social influence channels such as peer advice are being used to a greater extent for decision-making (Latreche et al., 2024; Song et al., 2023; Kaur, 2018; Lusardi and Mitchell, 2014). Online financial learning through tutorials, apps or webinars has empowered consumers by improving knowledge and perceived control, while peer advice has replaced formal advice services, especially among millennials and tech-savvy consumers (Akhter and Hoque, 2022; Sivaramakrishnan et al., 2017). The change demonstrates a move towards information-mediated investment behavior, where both cognitive and social inputs interact to form intention.

In these behavioral changes, PU—a key concept of the Technology Acceptance Model (Davis, 1989)—is a key explanation factor. It encompasses the idea that a technology, content, or recommendation can add value to the investing process (Teo, 2011; Kim and Lee, 2008). Although technology adoption is a key issue, its mediating role in finance has hardly been empirically researched. Even fewer have investigated how DFE and peer feedback together influence PU and thus purchase intention (Deb et al., 2025; Mishra et al., 2023; Venkatesh and Davis, 2000).

Most previous studies analyse awareness, subjective norms or platform acceptance in isolation (Kaur and Kaushik, 2016; Hafit et al., 2020), but without combining educational, technological, and social predictors in a complete model. The COVID-19 pandemic also emphasises the importance of self-directed financial literacy, with investors increasingly using online information sources and social peers (Goodell, 2020; Saxena et al., 2023). Although digital awareness has been found to have a positive impact on attitudes (Sivaramakrishnan et al., 2017; Zhang et al., 2024), the literature is sparse in estimating its indirect effect by way of PU.

With these developments, this study intends to bridge the knowledge gap by investigating the interaction effect of e-financial education and word-of-mouth on mutual fund buying intention, moderated by PU. The model draws from TAM and behavioral finance to suggest an enhanced model for contemporary investors (Davis, 1989; Venkatesh and Davis, 2000; Mishra et al., 2023). By tackling the following research questions, we hope to add fresh perspectives to the body of existing literature in this paper:

2.1. Research Questions

RQ1: Does DFE significantly influence mutual fund purchase intention?
RQ2: To what extent do recommendations influence mutual fund purchase intention to buy investment funds?
RQ3: To what extent does PU moderate the investment fund buying intention and DFE relationship?
RQ4: Is PU a mediator between PRs and mutual fund intention to purchase?
RQ5: To what extent are peer influences contrasted with educational influences in predicting PU?
RQ6: How can FinTech platforms use these learnings to drive digital uptake of mutual fund offerings?

2.2. Development of Hypothesis

2.2.1. Digital financial education and purchase intention

In investment decision-making, a stronger intention involves a higher likelihood of investment behavior. DFE is one of the new determinants of investment intentions and refers to knowledge and awareness that individuals create through digital media such as interactive financial products, webinars, mobile apps, and online tutorials. These media simplify complex financial knowledge, build confidence, and overcome cognitive barriers to investment (Koskelainen et al., 2023; Jou et al., 2023). Those who are financially educated will be able to recognize the pros and cons of mutual fund investment and improve the quality of their decision. Learning modes through digital formats have been found to generate goal-based financial planning and reduce investment inertia (Kaur, 2018; Fang et al., 2022; Alperovych et al., 2024). DFE is hence positively effective in the psychological preparedness of an investor and investment intention. Those who are more exposed to DFE are probably more inclined to buy an investment fund.

H_1: DFE has a significant positive influence on mutual fund purchase intention.

2.2.2. Peer recommendations and purchase intention

PRs—endorsements and recommendations from family and friends or online forums—have emerged as significant cues to prospective investors. Investors employ peers not just as information assistance but also to economize on cognitive effort and perceived risk, especially when they lack experience (Xu et al., 2022; Patel et al., 2024). As Koç Ustali et al. (2025) show, peer and friend communication channels (e.g., Twitter, Telegram) have a direct impact on investment intentions and attitudes, especially for those investors with no previous experience of investments. Experienced investors may use individual research, but novice investors believe more in social interactions and PRs. This peer influence is facilitated in cases where community-based trust controls or private messaging exist, and this creates a positive perception that builds more intense behavior intent (Palamida et al., 2017; Burciu et al., 2020). From this evidence, mutual fund buying intention is expected to be affected significantly by peer advice, especially when transmitted via digital social media.

H_2: PRs have a significant positive influence on mutual fund purchase intention.

2.2.3. Digital financial education and perceived usefulness

PU refers to "the extent to which an individual believes that using a given system enhances his or her performance or decision-making." According to the TAM, PU is the most potent cognitive determinant of a person's behavioral intention to embrace financial technology solutions. Financial education in digital format (DFE)—its skills and knowledge required for the use of digital financial services for access, evaluation, and utilization—has been identified as a significant determinant of users' experience with FinTech platforms and investment instruments (Zait and Bertea, 2015; Amnas et al., 2024). Especially for inexperienced investors, DFE strengthens confidence in the user-friendliness of such tools and also improves users' skills in dealing with investment interfaces and analysing

financial products (Kakinuma, 2022; Ravikumar et al., 2022). Investors are more likely to see digital financial products as helpful in achieving their financial goals if they understand how they work and believe they are less risky. According to recent empirical research, digital financial literacy has a major impact on the acceptance of FinTech services and perceived benefits, which in turn improve user interactions (He et al., 2024; Gautam et al., 2022). In line with industry fundamentals and empirical findings, it is assumed that digital financial literacy significantly increases the PU of digital investment platforms.

H_3: DFE has a significant positive influence on PU.

2.2.4. Peer recommendations and perceived usefulness

In TAM, social influence—PRs are no exception—has appeared time and again as a key driver of PU (Davis, 1989; Holden and Karsh, 2010). PRs provide reassurance, reduce effortful mental processes, and give confidence, especially when individuals lack confidence in a decision, such as an investment. The work of Haverila et al. (2023) also establishes a good and significant positive relationship between social influence and PU. In their use of TAM in non-pharmaceutical interventions, recommendations from family and friends were found to significantly enhance people's perceptions of usefulness for health-related behaviors. Applying this conclusion to a financial environment, it is logical to assume that PRs on mutual fund platforms increase PU, i.e. for new investors seeking familiarity and social support (Koenig et al., 2004; Zhang et al., 2020). Therefore, it is suggested that PRs act as a cognitive anchor and increase the perceived benefits of using mutual fund applications and platforms.

H_4: PRs have a significant positive influence on PU.

2.2.5. Perceived usefulness and purchase intention

As one of the central pillars of the TAM, PU exerts a robust influence on behavioural intention in all digital contexts (Venkatesh and Davis, 2000; Teo, 2011). In the mutual funds context, PU captures to what extent an investor considers digital channels—e.g., a mobile app or robo-advisors—to help make investment decisions. If the users view digital channels as effective for offering quality fund comparisons, portfolio tracking, and efficient procedures, they are more likely to intend to invest (Kim and Lee, 2008; Deb et al., 2025). Hadi Putra et al. (2022) found that PU has a great impact on user retention for mutual fund investment apps, especially in conjunction with perceived enjoyment and system quality. Similarly, Zait and Bertea (2015) pointed out that PU is a more accurate predictor than ease of use in financial decision-making. PU is therefore a crucial cognitive factor that influences the intention to buy technology-based mutual funds.

H_5: PU has a significant positive influence on mutual fund purchase intention.

2.2.6. Perceived usefulness as a mediator

DFE is the core of building investors' competence and clarity, especially among young or new investors. When presented through gamified apps, explainer videos or structured online courses, it not only builds financial skills but also increases PU by reducing complexity and increasing control over finances (Zait and Bertea, 2015; Mishra et al., 2024). The greater the usefulness they see from such kinds of resources, the more likely they will be to utilize mutual fund platforms. Empirical evidence supports the argument that PU is a robust mediator of digital financial literacy and investment intention by promoting perceived effectiveness in utilizing investment platforms and tools (Amnas et al., 2024; Ravikumar et al., 2022).

Similarly, PRs—typically transmitted via social media, forums, and messaging apps—serve as mental shortcuts that reduce uncertainty and enhance confidence (Rohden and Espartel, 2024; Palamida et al., 2017). Such PRs, especially if from familiar and credible sources, affect judgments about the credibility and functional value of investment platforms, and this enhances PU. PU has been found to be supported by social validation processes, hence boosting behavioral intention (Haverila et al., 2023; Zhang et al., 2020). Essentially, PU supports the translation of peer messages into knowledgeable investment behavior due to increased perceived relevance and utility of mutual fund tools. Therefore, PU is an effective mediation process through which both e-finance education and word of mouth influence the purchase intention for an investment fund. Not only does the mediation effect support TAM, but recent studies on behavioural economics also emphasise cognitive evaluation as a precursor to financial decisions (Mishra et al., 2023; Deb et al., 2025).

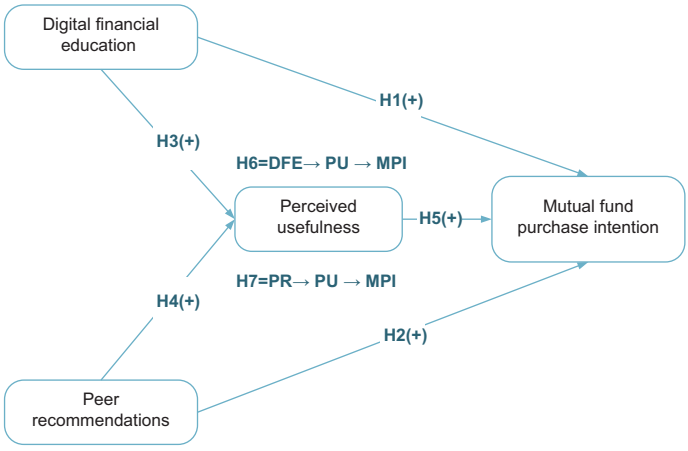
H_6: PU mediates the relationship between DFE and mutual fund purchase intention.

H_7: PU mediates the relationship between PRs and mutual fund purchase intention.

2.3. Conceptual Framework

The suggested conceptual model in this study is depicted in Figure 1, which investigates how PR and online financial education affect the intention to buy a mutual fund with PU as a mediator. The hypothesis posits that DFE directly influences mutual fund purchase intention (H_1), and indirectly impacts PU (H_3), which in turn has a significant influence on purchase intention (H_5). This points towards a dual channel—direct and indirect—through which DFE influences investment behavior. The indirect channel

Figure 1: The conceptual model



(Source: The authors)

is represented by H_6, wherein PU is a mediator of DFE on mutual fund purchase intention. Equally, PR are predicted to have a direct effect on purchase intention (H_2) and to have a positive effect on PU (H_4). This, once again, creates an indirect route (H_7), such that PU is mediating the effect of PRs on purchase intention of mutual funds. Combined, the model draws on elements of the TAM and behavioral finance, estimating PU as a critical cognitive mediator in modeling external informational inputs (education and peer influence) to behavioral intent.

3. METHODOLOGY

3.1. Data Collection

In order to achieve robust and region-wise balanced outcomes, the current work utilized a multi-stage stratified random sampling technique covering South Indian states, i.e., Tamil Nadu, Karnataka, Kerala, Andhra Pradesh, and Telangana. Stratification was done on two major attributes: (i) geographic location (urban or rural) and (ii) levels of digital penetration, both of which are significant determinants of digital financial behavior. In the first stage, all five South Indian states were taken as individual strata. In the second stage, the districts were randomly selected in each state with representation from both urban and semi-urban/rural areas. In the third phase, individual respondents were selected using snowball and random sampling to ensure that respondents were familiar with financial services or had an interest in investment fund products. Given the constant need for electronic communication and to optimize reach and convenience, data was collected via a structured online questionnaire on Google Forms. Email, financial education groups, mobile apps, and social media sites like Telegram and WhatsApp were all used to disseminate the survey link. Screening questions were incorporated in the questionnaire to assess respondent qualification (i.e., aged 18 years and older, residing in South India, and having basic knowledge or experience of digital financial platforms). The data collection took place between 15 April 2025 and 15 June 2025. 340 complete responses were used for the final analysis after inconsistent and incomplete responses were eliminated. In terms of sampling adequacy, the structural model included 4 latent constructs, and based on the rule of thumb ($N \geq V^2 + 50$), a minimum of 66 responses was required (Hair et al., 2011; Kock and Hadaya, 2018). In addition, the G*Power analysis was defined with the following settings: Statistical power (1-β) = 0.80, significance level $\alpha = 0.05$, and effect size $f^2 = 0.15$ (medium). The result was a minimum sample size of 184 respondents to detect medium effects (Cohen, 1988). Therefore, the final sample of 340 responses more than adequately meets and encompasses these requirements, and accordingly, there is enough statistical power for hypothesis testing. This approach ensured that the data not only documented varied populations but was also relevant to the study objectives, recording attitudes and intentions to act that were shaped by digital financial literacy and social influence in a changing financial landscape of South India.

3.2. Measures

In order to ensure content validity, all measurement points were taken from already validated instruments in the literature and tailored to the area of investment funds. The questionnaire was originally designed in English and structured to capture both demographic and attitudinal variables. Full details of the measurement items and their sources are provided in Table 1. Demographic details such as gender were measured using a nominal scale, while age and education level were assessed using 4-point ordinal scales. Monthly income was measured using a 5-point interval scale. The constructs of PU, DFE, PRs, and mutual fund purchase intention were measured using a 5-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree." Because shorter Likert scales have been demonstrated to lower cognitive load and avoid respondent fatigue, a 5-point scale was selected rather than a 7-point one (Padmavathy et al., 2019). To minimise potential methodological bias, different types of scales were used in the different sections of the questionnaire. The original version of the questionnaire was pre-tested with two subject matter experts and ten postdoctoral researchers. Based on their feedback, minor adjustments were made to the wording to improve clarity and relevance, particularly in the wording of the questions on investment intention and PU of digital platforms. Construct names, codes, items, and literature sources are listed in Table 2.

3.3. Demographics

The respondents' demographic profile is shown in Table 1. Most were male (64.12%) and aged 18-29 years (81.18%), representing a youthful sample. Educationally, most held a postgraduate degree (47.65%), followed by graduates (37.65%). Nearly half (49.41%) earned an annual income of under ₹2,40,000. The occupation showed working professionals (45.29%) as the largest, followed by students (35.88%). Further, urban residents accounted for 70% of the sample, representing greater digital access among them.

3.4. Common Method Bias

Since data for both independent and dependent variables were collected from a self-reporting questionnaire using a single-instrument method, there was a threat of common method bias (CMB) to confirm the findings. The single-factor test of Harman

Table 1: Demographic profile

Variable	Category	(n)	Percentage
Gender	Male	218	64.12
	Female	122	35.88
Age group (years)	18-29	276	81.18
	30-39	36	10.59
	40-49	18	5.29
	50 and above	10	2.94
Education level	Graduation	128	37.65
	Post-graduation	162	47.65
	Doctorate	24	7.06
	Others (diploma/12th/etc.)	26	7.65
Annual income	Below ₹2,40,000	168	49.41
	₹2,40,000-₹4,80,000	72	21.18
	₹4,80,000-₹6,00,000	38	11.18
	₹6,00,000-₹12,00,000	42	12.35
	Above ₹12,00,000	20	5.88
Occupation	Student	122	35.88
	Working professional	154	45.29
	Self-employed	42	12.35
	Others	22	6.47
Location	Urban	238	70.00
	Rural/semi-urban	102	30.00

Table 2: Questionnaire

Construct	Code	Measurement items	Source (s)
Digital financial education	DFE1	I have accessed educational content about mutual funds through digital platforms (e.g., apps, YouTube).	Lusardi and Mitchell (2014); Sivaramakrishnan et al. (2017)
	DFE2	I understand mutual fund investment basics through online sources.	
	DFE3	Digital platforms have improved my understanding of risk and return in mutual fund investing.	
	DFE4	I feel more confident to invest in mutual funds after attending webinars or reading online content.	
Peer recommendations	PRC1	I consider mutual fund suggestions made by friends or family.	Palamida et al. (2017); Burciu et al. (2020)
	PRC2	I rely on online peer discussions (e.g., WhatsApp, Telegram, forums) before investing in mutual funds.	
	PRC3	I trust peer recommendations more than company advertisements.	
Perceived usefulness	PU1	Mutual fund investment helps me plan my financial future effectively.	Davis (1989); Brahmana et al. (2018)
	PU2	Investing in mutual funds improves my personal financial management.	
	PU3	Mutual fund apps and platforms simplify my investment process.	
Mutual fund purchase intention	PI1	I intend to invest in mutual funds in the near future.	Mishra et al. (2023); Ajzen (1991)
	PI2	I will recommend mutual fund investment to others.	
	PI3	I am likely to continue investing in mutual funds in the long run.	

was first conducted using SPSS. The unrotated factor solution indicated that the variance explained by the first factor was only 26.84%, much below the 50% threshold, indicating common method variance cannot be a major concern (Podsakoff et al., 2003). Additionally, in SmartPLS version 4, there was a full collinearity check where the VIF values for all the constructs were considered. According to Kock (2015), a VIF value below 3.3 indicates that the model is free from vertical and lateral collinearity and suggests the absence of common method bias. For this study, latent variables for all were calculated as having VIF values ranging from 1.62 to 2.74, ensuring that CMB is not a significant factor. With the above results, it is safe to conclude that common method bias does not taint the model estimates.

3.5. Data Analysis

PLS-SEM with SmartPLS 4.0 was used to analyze the data gathered for this study. PLS-SEM is a variance-based structural modelling technique that is particularly well suited for predictive research, theory development and exploratory studies with highly complex models and numerous pathways and constructs (Hair et al., 2021a). Given that the goal of this study is to investigate the direct and indirect (mediated) interrelations among DFE, PRs, PU, and mutual fund purchase intention, PLS-SEM was found to be appropriate.

Unlike covariance-based SEM (CB-SEM) approaches such as LISREL or AMOS, which require larger samples and place a greater emphasis on model fit and theory testing than others, PLS-SEM is less rigid with moderate or small sample sizes and non-normal data distribution (Hair et al., 2011). PLS-SEM also allows for both formative and reflective constructs to be analyzed at the same time and grants more leeway in the management of complex mediation models, which was essential for our conceptual framework.

PLS algorithm was executed to forecast the outer loadings of the indicators, path coefficients, and R^2 for the endogenous constructs. The bootstrapping technique (with 5,000 subsamples) was employed to ascertain the significance of direct and indirect paths and to test if PU mediates. Core model estimation metrics were composite reliability (CR), average variance extracted (AVE) as an indicator of convergent validity, and Fornell-Larcker criterion and HTMT ratio as indicators of discriminant validity. R^2, Q^2, and effect sizes (f^2) were the structural model estimation metrics. This approach to analysis is in agreement with past research in FinTech adoption, mutual fund behavior, and behavioral intention models (e.g., Mishra et al., 2023; Deb et al., 2025), where PLS-SEM was applied in the exploration of complex causal relations as well as mediation effects. Thus, the use of SmartPLS 4.0 and PLS-SEM methodology forms a comprehensive and reliable analysis of the hypothesized model, both ensuring theoretical robustness and practical relevance.

4. RESULTS

To perform structural model and measurement analyses, we employed the PLS-SEM. The data analysis for this study was conducted using Smart PLS version 4.0 (Hair et al., 2019).

4.1. Assessment of Measurement Model

Structural equation modelling (SEM) relies on the stability of the measurement model, which ensures the validity and reliability of the constructs used in the structural model (Hair et al., 2021b). The measurement model was tested using SmartPLS 4 and the results are presented in Tables 3 and 4.

Cronbach's alpha and composite reliability (CR) were calculated to guarantee internal consistency. Standard practice has proved that a construct would be reliable if these measures were above the recommended cut-off of 0.70 (Henseler et al., 2016). As shown in Table 3, the reliability and internal consistency of all the constructs were ensured by Cronbach's alpha values of 0.755-0.837 and composite reliability (rho_c) values of 0.845-0.902. Convergent validity was determined by applying the average variance extracted (AVE), which should be above the lower limit of 0.50 (Hair et al., 2021b). All AVE values ranged from 0.577 (digital financial literacy) to 0.754 (PU), confirming that all constructs explained more than 50% of the variance of the observed indicators. Convergent validity was, therefore, established in all the latent variables. Figure 2 displays the measurement model with factor loading.

Figure 2: Measurement model with factor loading

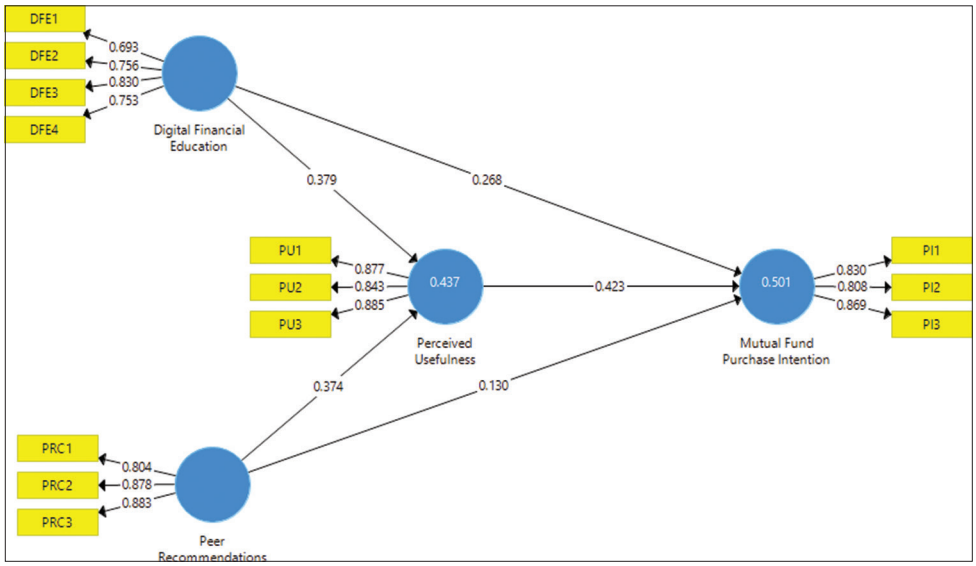


Table 3: Convergent validity and reliability

Construct	Items	Loading	Cronbach's ∝	CR (rho_a)	CR (rho_c)	AVE
Digital financial education	DFE1	0.693	0.755	0.769	0.845	0.577
	DFE2	0.756				
	DFE3	0.830				
	DFE4	0.753				
Peer recommendations	PRC1	0.804	0.817	0.825	0.891	0.732
	PRC2	0.878				
	PRC3	0.883				
Perceived usefulness	PU1	0.877	0.837	0.839	0.902	0.754
	PU2	0.843				
	PU3	0.885				
Mutual fund purchase intention	PI1	0.830	0.784	0.786	0.874	0.699
	PI2	0.808				
	PI3	0.869				

Table 4: Discriminant validity: Fornell-Larcker criterion

	DFE	PI	PR	PU
DFE	0.76			
PI	0.584	0.836		
PR	0.543	0.52	0.856	
PU	0.582	0.654	0.579	0.868

To examine discriminant validity, the Fornell-Larcker criterion was employed (Fornell and Larcker, 1981). According to this criterion, the square root of AVE (diagonal values in Table 4) must be greater than the correlation values among the constructs (off-diagonal values). All diagonal values—0.76 (DFE), 0.836 (PI), 0.856 (PR), and 0.868 (PU)—in Table 4 are greater than their corresponding inter-construct correlations, thus demonstrating discriminant validity according to Hair et al. (2021b).

4.2. Assessment of the Structural Model

Following confirmation of the measurement model's validity and reliability, the structural model was evaluated to validate the hypotheses that were established. Table 5 shows the results of hypothesis testing, while Figure 3 illustrates the structural model with the T-values indicating the strength and significance of every path relationship.

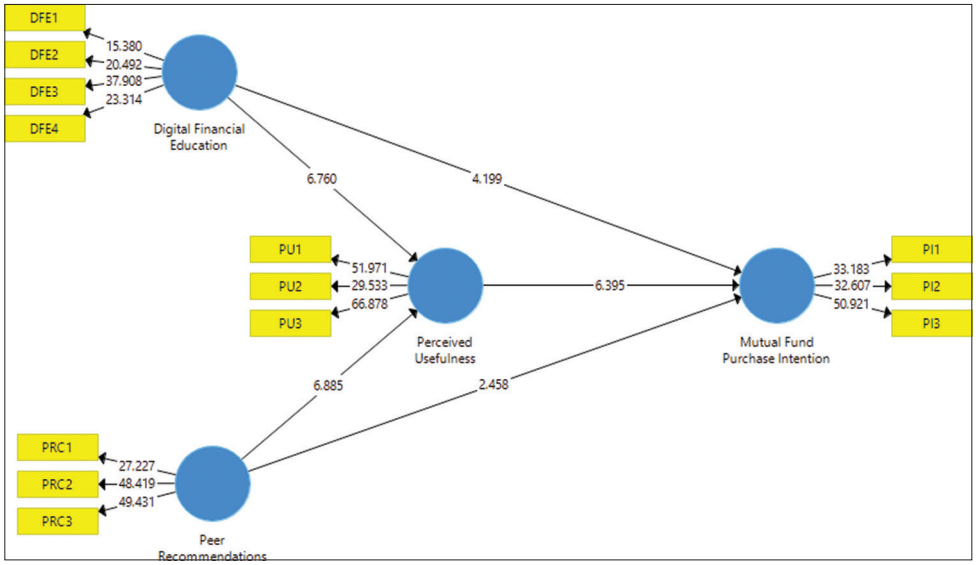
The findings indicated that DFE had a significant and positive effect on PI ($\beta = 0.268$, $P < 0.001$), thereby confirming H_1. Similarly, PR also had a significant effect on Purchase Intention ($\beta = 0.130$, $P < 0.05$), thereby confirming H_2. The results show that both educational and social cues have a strong impact on the intention to invest in mutual funds in a digital environment. In addition, DFE was found to have a significant impact on PU (PU) ($\beta = 0.379$, $P < 0.001$), which in turn is influenced by PR, which has a significant impact on PU ($\beta = 0.374$, $P < 0.001$), supporting H_3 and H_4, respectively. These results show that both formal digital education and peer influence improve investors' perceptions of the usefulness of digital platforms for making informed investment fund decisions. As the TAM predicted, PU significantly and statistically significantly influenced PI ($\beta = 0.423$, $P < 0.001$), supporting H_5. This is consistent with the central TAM hypothesis that the PU of a system influences PI. Most importantly, mediation analysis revealed that PU significantly mediated the relationship between DFE and PI ($\beta = 0.160$, $P < 0.001$) and also between PR and PI ($\beta = 0.158$, $P < 0.001$), supporting H_6 and H_7, respectively. This suggests that the influence of DFE and PR on PI occurs in part by increasing the PU of mutual fund websites.

Table 5: Findings from the testing of hypotheses

Hypothesis	Path	β (original sample)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-values	Decision
H_1	DFE→PI	0.268	0.064	4.199	0.000	Supported
H_2	PR→PI	0.130	0.053	2.458	0.014	Supported
H_3	DFE→PU	0.379	0.056	6.76	0.000	Supported
H_4	PR→PU	0.374	0.054	6.885	0.000	Supported
H_5	PU→PI	0.423	0.066	6.395	0.000	Supported
H_6	DFE→PU→PI	0.160	0.037	4.333	0.000	Supported (mediation)
H_7	PR→PU→PI	0.158	0.031	5.151	0.000	Supported (mediation)

***P<0.001

Figure 3: Structural model with T-value



To evaluate the explanatory capability of the structural model, R-squared (R^2) measures were considered for endogenous constructs. As seen in the results, the model explains 50.1% variance in PI ($R^2 = 0.501$) and 43.7% variance in PU ($R^2 = 0.437$). These values are above the minimum value of 0.10 recommended by Falk and Miller (1992) for endogenous constructs, which indicates a high degree of explanatory power and model fit. PU and PI had the strongest correlation (r = 0.201), followed by DFE and PU (r = 0.180) and PR and PU (r = 0.175), according to the inter-construct correlation matrix. Such relationships also empower the hypothesized model paths. In order to assess predictive validity of the model, the Stone-Geisser Q^2 values (blindfolding procedure) were computed. Although values for Q^2 are not given in the provided data, as per Hair et al. (2021A), Q^2 values greater than zero for endogenous constructs confirm that the model possesses good predictive validity. In the present study, as all endogenous variables possess $R^2 > 0.40$, one can confidently say that the model possesses a good predictive validity.

5. DISCUSSION

This study sought to examine DFE and PR's direct and indirect impacts on PI under the theoretical structure of the TAM. The results of the structural model analysis provided strong empirical validation for all the hypothesized associations, revealing valuable insights into the behavior of digital mutual fund investors in South India.

Firstly, the statistical significance of the direct effect of DFE on PI (H_1) indicates that the provision of digital learning platforms for finance increases investors' confidence and positively affects their investment intention. The finding corroborates earlier research pointing to the role of digital literacy in promoting active investment behavior (Mishra et al., 2024; Koskelainen et al., 2023). PR positively influenced PI (H_2), validating that social interactions and peer word-of-mouth continue to be powerful drivers of investment intention. The increasing use of channels such as WhatsApp, Telegram, and financial forums confirms earlier findings showing that peer influence is replacing institutional advice in the majority of investment environments (Koç Ustali et al., 2025; Rohden and Espartel, 2024).

Moreover, both DFE and PR positively influenced PU (H_3 and H_4), supporting their function in establishing the cognitive appraisal of the usefulness of online mutual fund websites. This supports the TAM hypothesis that PU is not only influenced by system characteristics but also by contextual and social factors (Teo et al., 2015; Kim and Lee, 2008). As anticipated, PU strongly influenced PI (H_5), echoing the very premise of TAM and affirming that user perception of the efficacy of digital platforms as investing tools raises the behavioral intention. This result supports the finding of

Hadi Putra et al. (2022), who discovered PU to be the significant motivator of retention and engagement in mobile mutual fund platforms. The test of mediation identified that PU exerts a significant intervening effect between DFE and PR on PI (H_6 and H_7). These results resonate with the dual nature of PU, which serves both as an extrinsic factor and as a driver of intention. This adds to current knowledge since it empirically verifies PU as a cognitive channel whereby education and peer inputs are translated into investment intention.

This study adds to behavioral finance literature by integrating education and social influence variables within the TAM framework, enhancing knowledge of behavior to buy mutual funds online. The high explanatory power of the model (R^2 for PI = 0.501 and R^2 for PU = 0.437) means that policymakers and FinTech platforms must give priority to educational content material and peer interaction interventions to increase adoption and trust in mutual fund investment.

6. IMPLICATIONS

This study makes theoretical contributions in the following ways as it extends TAM in the context of mutual fund investment in a FinTech situation. By considering DFE and PR as exogenous variables and PU as an intervening cognition, the model offers a richer account of what drives PI among individual investors. Findings substantiate that educational and social antecedents are not only relevant but statistically significant in predicting the PU of online financial websites, thereby having an effect on behavioral outcomes. This contributes to TAM literature by situating it within the context of the adoption of mutual funds, where investment decision is predisposed towards being driven by asymmetry of knowledge and social influence. Secondarily, the study contributes to behavioral finance through the empirical confirmation of the mediating role of PU, therefore demonstrating the manner in which cognitive appraisal serves as a bridge between external informational cues and investor intention. These results contribute evidence towards the incorporation of cognitive and socio-environmental factors into the explanation of technology-mediated financial behavior.

In practice, the study presents recommendations that are actionable for FinTech providers, mutual fund houses, educators in finance, and regulators. The positive and significant effect of DFE on PU and PI would suggest that investment websites should include easy-to-use and interactive online learning resources — such as interactive tutorials, webinars, and modules of financial literacy — to facilitate user trust and comprehension. Second, the high level of influence in PR indicates that peer networks and social proof mechanisms such as referral systems, community features, and user feedback will play an important role in the adoption of mutual funds. As PU is a key mediator, platforms must prioritize user experience design that enhances PU through features such as real-time analytics, dashboards, and suggestions. The findings can be used by regulators and policymakers to encourage electronic financial inclusion by supporting initiatives that improve financial literacy and community-based financial engagement, particularly for 1st-time and young investors.

7. CONCLUSION

The current research offers significant insights into behavioral dynamics that influence the intention to invest in mutual funds through digital platforms among retail investors. Combining DFE and PR into TAM and testing the mediating role of PU, the research once again confirms that both cognitive and social antecedents are essential for PI. The results show that digital financial learning and peer-to-peer interaction increase the perceived benefits of investment platforms, which subsequently leads to stronger purchase intentions. The structural model showed high explanatory power, suggesting that a combination of educational ability and social influence is one of the main factors influencing FinTech adoption in the context of investments. The tested model offers a robust theoretical foundation for the conceptualization of digital investment behavior in emerging economies such as India.

8. LIMITATIONS AND FUTURE SCOPE

Although the study contributed, it is vulnerable to some limitations. First, the data were collected using self-report scales that are most likely to be vulnerable to social desirability bias. Secondly, the study was geographically limited to South India, which restricts the results' applicability to different geographic areas or demographic settings. Moreover, the study was based on the intention to buy mutual funds and not on actual investment behaviour. In future studies, longitudinal studies can be conducted to observe actual investment outcomes over time. A bigger sample size from multiple geographic regions and the inclusion of more moderator variables, such as digital confidence, risk appetite, or income level, can make the model stronger. Apart from this, comparison studies of rural or urban investors or cross-country studies can provide more insights about digital financial inclusion and investment behaviour in the global FinTech context.

REFERENCES

Ajzen, I. (1991), The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Akhter, T., Hoque, M.E. (2022), Moderating effects of financial cognitive abilities and considerations on the attitude-intentions nexus of stock market participation. International Journal of Financial Studies, 10(1), 5.

Ali, N., Alfayez, M. (2024), The impact of E-CRM on customer loyalty in the airline industry: The mediating role of customer experience. Cogent Business Management, 11(1), 2364838.

Ali-Rind, A., Boubaker, S., Jarjir, S.L. (2023), Peer effects in financial economics: A literature survey. Research in International Business and Finance, 64, 101873.

Alperovych, Y., Calcagno, R., Lentz, M. (2024), Entrepreneurs on their financial literacy: Evidence from the Netherlands. Venture Capital, 26(4), 377-400.

Amnas, M.B., Selvam, M., Parayitam, S. (2024), FinTech and financial inclusion: Exploring the mediating role of digital financial literacy and the moderating influence of perceived regulatory support. Journal of Risk and Financial Management, 17(3), 108.

Association of Mutual funds in India (AMFI). (2022), AMFI Quarterly Data April-December 2022. Available from: https://portal.amfiindia.com/spages/aqu-vol22-issuei.pdf

Brahmana, R.K., Brahmana, R.K.M., Memarista, G. (2018), Planned behaviour in purchasing health insurance. The South East Asian Journal of Management (SEAM), 12(1), 53-64.

Burciu, A., Kicsi, R., Bostan, I. (2020), Social trust and dynamics of capitalist economies in the context of clashing managerial factors with risks and severe turbulence: A conceptual inquiry. Sustainability, 12(21), 8794.

Chavali, K., Rosario, S. (2019), Influence of gender on investment decisions of investors in sultanate of Oman. Global Journal of Economics and Business, 7(2), 235.

Che Hassan, N., Abdul-Rahman, A., Ab. Hamid, S.N., Mohd Amin, S.I. (2024), What factors affecting investment decision? The moderating role of fintech self-efficacy. PLoS One, 19(4), e0299004.

Chen, F., Yu, D., Sun, Z. (2023), Investigating the associations of consumer financial knowledge and financial behaviors of credit card use. Heliyon, 9(1), e12713.

Choi, A., Stoutland, D., Blanco, L. (2024), An evaluation of a digital financial education program and the impact of COVID-19 on financial well-being among college students. Journal of American College Health, 72(9), 3690-3702.

Cohen, J. (2013), Statistical Power Analysis for the Behavioral Sciences. London: Routledge.

Davis, F.D. (1989), Technology acceptance model: TAM. In: Al-Suqri, M.N., Al-Aufi, A.S., editor. Information Seeking Behavior and Technology Adoption. United States: IGI Global. p205-219.

Deb, S.K., Jain, R., Manohar, S., Marwah, S. (2025), A study on mediation effect of relationship quality outcome between customer relationship management and mutual fund decision. Global Knowledge Memory and Communication, 74(1/2), 370-392.

Dubey, N.K., Sangle, P. (2019), Customer perception of CRM implementation in banking context: Scale development and validation. Journal of Advances in Management Research, 16(1), 38-63.

Falk, R.F., Miller, N.B. (1992), A primer for Soft Modeling. United States: University of Akron Press.

Fang, J., Hao, W., Reyers, M. (2022), Financial advice, financial literacy and social interaction: What matters to retirement saving decisions? Applied Economics, 54(50), 5827-5850.

Fornell, C., Larcker, D.F. (1981), Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Furrebøe, E.F., Nyhus, E.K. (2022), Financial self-efficacy, financial literacy, and gender: A review. Journal of Consumer Affairs, 56(2), 743-765.

Gao, J., Fan, C., Liu, T., Bai, X., Li, W., Tan, H. (2025), Embracing market dynamics in the post-COVID era: A data-driven analysis of investor sentiment and behavioral characteristics in stock index futures returns. Omega, 131, 103193.

Gautam, R.S., Rastogi, S., Rawal, A., Bhimavarapu, V.M., Kanoujiya, J., Rastogi, S. (2022), Financial technology and its impact on digital literacy in India: Using poverty as a moderating variable. Journal of Risk and Financial Management, 15(7), 311.

Goodell, J.W. (2020), COVID-19 and finance: Agendas for future research. Finance Research Letters, 35, 101512.

Goyal, K., Kumar, S. (2021), Financial literacy: A systematic review and bibliometric analysis. International Journal of Consumer Studies, 45(1), 80-105.

Hadi Putra, P.O., Nugroho, S., Hidayanto, A.N. (2022), Factors affecting user retention of mobile mutual fund investment applications: Evidence from Indonesia. Human Behavior and Emerging Technologies, 2022(1), 7521680.

Hafit, N.I.A., Othman, N.A.F., Rusdi, S.D., Mahpar, N.S., Sharie, M.F.I.M. (2020), The effects of perceived usefulness and perceived ease of use on acceptance towards office assistance application among employers to disabled employees. Advances in Business Research International Journal, 6(1), 107-115.

Hair, J.F. Jr., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S. (2021a), Partial Least Squares Structural Equation Modeling (PLS-SEM) using R: A Workbook. Berlin: Springer Nature. p197.

Hair, J.F., Astrachan, C.B., Moisescu, O.I., Radomir, L., Sarstedt, M., Vaithilingam, S., Ringle, C.M. (2021b), Executing and interpreting applications of PLS-SEM: Updates for family business researchers. Journal of Family Business Strategy, 12(3), 100392.

Hair, J.F., Ringle, C.M., Sarstedt, M. (2011), PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139-152.

Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M. (2019), When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

Haverila, M.J., McLaughlin, C., Haverila, K. (2023), The impact of social influence on perceived usefulness and behavioral intentions in the usage of non-pharmaceutical interventions (NPIs). International Journal of Healthcare Management, 16(1), 145-156.

He, H., Luo, W., Gong, Y., Berson, I.R., Berson, M.J. (2024), Digital financial literacy of young Chinese children in Shanghai: A mixed method study. Early Education and Development, 35(1), 57-76.

Henseler, J., Ringle, C.M., Sarstedt, M. (2016), Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405-431.

Holden, R.J., Karsh, B.T. (2010), The technology acceptance model: Its past and its future in health care. Journal of Biomedical Informatics, 43(1), 159-172.

Idrees, M.A., Ullah, S. (2024), Comparative analysis of FinTech adoption among Islamic and conventional banking users with moderating effect of education level: A UTAUT2 perspective. Journal of Open Innovation Technology Market and Complexity, 10(3), 100343.

Jou, Y.T., Shiang, W.J., Silitonga, R.M., Adilah, M., Halim, A.Z.A. (2023), Assessing factors that influence womenpreneurs' intention to use technology: A structural equation modeling approach. Behavioral Sciences, 13(2), 94.

Kakinuma, Y. (2022), Financial literacy and quality of life: A moderated mediation approach of FinTech adoption and leisure. International Journal of Social Economics, 49(12), 1713-1726.

Kasemharuethaisuk, H., Samanchuen, T. (2023), Factors influencing behavior intention in digital investment services of mutual fund distributors adoption in Thailand. Sustainability, 15(3), 2279.

Kaur, I. (2018), Mutual fund investor's behaviour towards information search and selection criteria: Do knowledge and perception about mutual funds matter? Qualitative Research in Financial Markets, 10(4), 395-414.

Kaur, I., Kaushik, K.P. (2016), Determinants of investment behaviour of investors towards mutual funds. Journal of Indian Business Research, 8(1), 19-42.

Kim, E., Kim, Y. (2025), Determinants of user acceptance of digital insurance platform service on InsurTech: An empirical study in South Korea. Asian Journal of Technology Innovation, 33(1), 45-75.

Kim, J., Lee, H.H. (2008), Consumer product search and purchase behaviour using various retail channels: The role of perceived retail usefulness. International Journal of Consumer Studies, 32(6), 619-627.

Koç Ustali, N., Kaya, A., Gürler, H.E., Buyukdag, N. (2025), The effect of the information channel on the investment decision: The bull and bear market and investment experience as a moderator. Australian Journal of Management, 50(1), 246-265.

Kock, N. (2015), Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration (IJEC), 11(4), 1-10.

Kock, N., Hadaya, P. (2018), Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, 28(1), 227-261.

Koenig, M.A., Clément, F., Harris, P.L. (2004), Trust in testimony: Children's use of true and false statements. Psychological Science, 15(10), 694-698.

Koskelainen, T., Kalmi, P., Scornavacca, E., Vartiainen, T. (2023), Financial literacy in the digital age-a research agenda. Journal of Consumer Affairs, 57(1), 507-528.

Kumar, P., Pillai, R., Kumar, N., Tabash, M.I. (2023), The interplay of skills, digital financial literacy, capability, and autonomy in financial decision making and well-being. Borsa Istanbul Review, 23(1), 169-183.

Kumar, S., Srivastava, M., Prakash, V. (2023), New horizons for industry 4.0 in modern business. In: Challenges and Opportunities for Mutual Fund Investment and the Role of Industry 4.0 to Recommend the Individual for Speculation. Berlin: Springer. p69-98.

Latreche, H., Bellahcene, M., Dutot, V. (2024), Does IT culture archetypes affect the perceived usefulness and perceived ease of use of e-banking services? A multistage approach of Algerian customers. International Journal of Bank Marketing, 42(7), 1760-1788.

Lee, J.M., Park, N., Heo, W. (2019), Importance of subjective financial knowledge and perceived credit score in payday loan use. International Journal of Financial Studies, 7(3), 53.

Lusardi, A., Mitchell, O.S. (2014), The economic importance of financial literacy: Theory and evidence. American Economic Journal Journal of Economic Literature, 52(1), 5-44.

Mishra, A.K., Bansal, R., Maurya, P.K., Kar, S.K., Bakshi, P.K. (2023), Predicting the antecedents of consumers' intention toward purchase of mutual funds: A hybrid PLS-SEM-neural network approach. International Journal of Consumer Studies, 47(2), 563-587.

Mishra, D., Agarwal, N., Sharahiley, S., Kandpal, V. (2024), Digital financial literacy and its impact on financial decision-making of women: Evidence from India. Journal of Risk and Financial Management, 17(10), 468.

Mou, J., Liu, W., Guan, C., Westland, J.C., Kim, J. (2024), Predicting the cryptocurrency market using social media metrics and search trends during COVID-19. Electronic Commerce Research, 24(2), 1307-1333.

Nicolescu, L., Tudorache, F.G. (2021), Investment behaviour in mutual funds: Is it a knowledge-based decision? Kybernetes, 50(10), 2726-2752.

Nilsson, J., Carlsson Hauff, J., Carlander, A. (2024), How consumers evaluate costs in complex services: The case of mutual fund fees. European Journal of Marketing, 58(13), 56-80.

Nugraha, D.P., Setiawan, B., Nathan, R.J., Fekete-Farkas, M. (2022), FinTech adoption drivers for innovation for SMEs in Indonesia. Journal of Open Innovation Technology Market and Complexity, 8(4), 208.

Padmavathy, C., Swapana, M., Paul, J. (2019), Online second-hand shopping motivation-Conceptualization, scale development, and validation. Journal of Retailing and Consumer Services, 51, 19-32.

Palamida, E., Xanthopoulou, D., Papagiannidis, S., Stamati, T. (2017), Exploring intentions towards human, social and financial capital investments in a turbulent economic environment. The International Journal of Entrepreneurship and Innovation, 18(2), 79-90.

Patel, V.V., Pandit, R., Sama, R. (2024), Understanding the impact of fashion app emotional attachment on consumer responses: The role of e-servicescape, customer experience and perceived value of online shopping. Journal of Fashion Marketing and Management an International Journal, 28(3), 581-601.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., Podsakoff, N.P. (2003), Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879.

Pyo, T.H., Lee, J.Y., Park, H.M. (2022), The effects of consumer preference and peer influence on trial of an experience good. Journal of Marketing Research, 59(6), 1161-1178.

Ravikumar, T., Suresha, B., Prakash, N., Vazirani, K., Krishna, T.A. (2022), Digital financial literacy among adults in India: Measurement and validation. Cogent Economics and Finance, 10(1), 2132631.

Rohden, S.F., Espartel, L.B. (2024), Consumer reactions to technology in retail: Choice uncertainty and reduced perceived control in decisions assisted by recommendation agents. Electronic Commerce Research, 24(2), 901-923.

Saxena, N., Gera, N., Taneja, M. (2023), An empirical study on facilitators and inhibitors of adoption of mobile banking in India. Electronic Commerce Research, 23(4), 2573-2604.

Sivaramakrishnan, S., Srivastava, M., Rastogi, A. (2017), Attitudinal factors, financial literacy, and stock market participation. International Journal of Bank Marketing, 35(5), 818-841.

Song, Y.A., Zhang, L., Ma, L., Bose, I. (2023), What shall I learn? Two-stage decision making under social influence on corporate E-learning platforms. Decision Support Systems, 171, 113978.

Suresh, G. (2024), Impact of financial literacy and behavioural biases on investment decision-making. FIIB Business Review, 13(1), 72-86.

Tajvidi, M., Wang, Y., Hajli, N., Love, P.E. (2021), Brand value Co-creation in social commerce: The role of interactivity, social support, and relationship quality. Computers in Human Behavior, 115, 105238.

Teo, A.C., Tan, G.W.H., Ooi, K.B., Hew, T.S., Yew, K.T. (2015), The effects of convenience and speed in m-payment. Industrial Management and data Systems, 115(2), 311-331.

Teo, T. (2011), Factors influencing teachers' intention to use technology: Model development and test. Computers Education, 57(4), 2432-2440.

Venkatesh, V., Davis, F. D. (2000), A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science, 46(2), 186-204.

Vörös, Z., Szabó, Z., Kehl, D., Kovács, O.B., Papp, T., Schepp, Z. (2021), The forms of financial literacy overconfidence and their role in financial well-being. International Journal of Consumer Studies, 45(6), 1292-1308.

Xu, Z., Li, Y., Hao, L. (2022), An empirical examination of UTAUT model and social network analysis. Library Hi Tech, 40(1), 18-32.

You, Y., Yu, Z., Zhang, W., Lu, L. (2023), FinTech platforms and mutual fund markets. Journal of International Financial Markets Institutions and Money, 84, 101652.

Zait, A., Bertea, P.E. (2015), Financial literacy-Conceptual definition and proposed approach for a measurement instrument. The Journal of Accounting and Management, 4(3), 37-42.

Zhang, P., Lv, Z.X., Liu, J.Y. (2024), Flows, performance, and investor behavior: Evidence from mutual funds in China. Cogent Economics Finance, 12(1), 2373258.

Zhang, X., Wang, F., Zhu, C., Wang, Z. (2020), Willingness to self-isolate when facing a pandemic risk: Model, empirical test, and policy recommendations. International Journal of Environmental Research and Public Health, 17(1), 197.