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Drivers of non-fungible token (NFT) investment intention: the roles of innovativeness, knowledge, subjective norms and perceived value

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Abstract

Purpose – This study explores key factors influencing individuals' intentions to invest in NFTs, focusing on personal innovativeness, reward sensitivity, knowledge, subjective norms, perceived value and perceived risk. The aim is to provide insights into what motivates investors within this emerging market, addressing a gap in the understanding of NFT adoption from an investor perspective.

Design/methodology/approach – An online survey collected data from 272 participants in China and Hong Kong. The research employs partial least squares-structural equation modeling (PLS-SEM) to assess the relationships between various individual, social and market factors and NFT investment intentions.

Findings – The results suggest that personal innovativeness, reward sensitivity, NFT knowledge, subjective norms and perceived value positively impact NFT investment intentions. Additionally, age and income moderate the effects of subjective norms and perceived value on investment intentions, highlighting demographic influences.

Practical implications – For practitioners, insights into investor motivators can inform strategies to promote NFT investments, such as promoting the high reward potential, enhancing investor knowledge, leveraging social proof and emphasizing NFTs' perceived value. For academics, the findings open pathways for further research into investor psychology and the evolving dynamics of NFT and traditional investment markets.

Originality/value – This study advances NFT literature by identifying determinants of NFT investment behavior, a relatively uncharted area. By incorporating theories from investment behavior and technology adoption, it provides a new framework to understand the psychological and social drivers specific to NFT investments.

Keywords Knowledge, Subjective norm, Non-fungible token, Perceived value, Personal innovativeness, Reward sensitivity

Paper type Research paper

Introduction

Non-Fungible Token (NFT) represents a cutting-edge application of blockchain technology, offering a means to certify ownership and authenticity of digital content (Wang, Li, Wang, & Chen, 2021). Unlike crypto-assets such as Bitcoin or Ethereum, which are fungible and interchangeable, NFTs embody unique digital entities (Dowling, 2022). These entities encompass various forms, including text, images, sound files or videos (Wilson, Karg, & Ghaderi, 2022). Consequently, NFTs are not merely subsets of digital assets but signify a broader ecosystem that combines creativity with ownership authenticity.

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A key distinction between NFTs and crypto currencies lies in their market dynamics and utility. While cryptocurrencies are primarily used for transactions, as store of value or for decentralized financial operations, NFTs have established their position within creative industries, gaming and digital arts (Jain, Bruckmann, & McDougall, 2022). This development has contributed to the rise of an emerging market with a high degree of independence from the cryptocurrency ecosystem (Bao & Roubaud, 2022). According to Gherghelas (2023), the trading volume of NFT is reaching US$946 million in January 2023. The investment volume in NFTs is expected to increase to around US $2.38 billion in 2024, compared to US $656 million in 2021 (Statista, 2023, April).

Another key characteristic of NFTs is their unique positioning in the investment landscape. Traditional investment tools, such as stocks and bonds, are evaluated based on their financial returns and intrinsic value tied to physical and corporate fundamentals. In contrast, NFTs derive value from digital provenance and the psychological appeal of creativity and ownership (Sestino, Guido, & Peluso, 2022). Thus, NFTs combine financial considerations with aesthetic and social drivers. Similar to certain alternative investment tools, NFTs offer both high market volatility and portfolio diversification opportunities due to their low correlation with those of conventional financial assets (Dowling, 2022).

The growing popularity of NFTs can be attributed to several factors, including the gradual acceptance of cryptocurrencies, emerging trends in popular culture and a surge in digital investments (Nadini *et al.*, 2021; Philippas, Rjiba, Guesmi, & Goutte, 2019). Moreover, their increasing transaction numbers and prices have been driven by high market volatility, low barriers to entry and investors' pursuit of speculative assets (Baker, Pizzo, & Su, 2022; Lee, Yan, & Wang, 2021). However, despite this enthusiasm, NFTs face significant challenges, such as environmental concerns arising from blockchain's energy consumption, regulatory ambiguities and fluctuating valuations (Ali *et al.*, 2023). These challenges highlight the need for a deeper understanding of the psychological and social factors influencing NFT investment behavior, which remains underexplored in the literature.

Previous studies of NFTs have primarily focused on pricing dynamics (Dowling, 2022) and economic value (Ko, Son, Lee, Jang, & Lee, 2022). Some researchers have also explored the relationship between NFTs and other financial products (Aharon & Demir, 2022). There has been a lack of research on the key factors that investors consider when purchasing NFTs, such as investor personality, perceived values and situational circumstances (Fortagne & Lis, 2023). This study addresses this gap by examining the determinants of NFT investment intentions. By integrating constructs such as personal innovativeness, reward sensitivity, knowledge, subjective norms, perceived values and perceived risk, it provides a robust framework for understanding what drives investors to adopt NFTs. These findings not only offer empirical insights into an emerging area of research but also provide practical implications for NFT platforms, marketers, financial institutions and other stakeholders aiming to promote investments in this domain.

Theoretical framework and development of hypotheses

This study builds upon previous research on cryptocurrencies and individual investment behavior to investigate the factors influencing individuals' intention to invest in NFTs. NFT purchases can be motivated by different perspectives, including those of investors, collectors and general consumers. Investors primarily view NFTs as financial assets, assessing their potential for monetary returns, portfolio diversification and market speculation (Ko *et al.*, 2022). Conversely, collectors are drawn to NFTs for their aesthetic appeal, cultural significance and uniqueness of NFTs, often prioritizing personal satisfaction and social signaling over financial gains (Sestino *et al.*, 2022). General consumers view NFTs as digital goods that enhance experiences in areas such as gaming, virtual environments or digital identity (Wilson *et al.*, 2022). This study focuses on the investor perspective, as the determinants of financial decision-making differ fundamentally from those influencing collecting or consumption behavior.

According to Che Hassan, Abdul-Rahman, Mohd Amin, and Ab Hamid (2023), several key theoretical perspectives are utilized to investigate investment intentions. The Theory of Planned Behavior (TPB) is prominently applied to examine individuals' intentions to invest, highlighting the relationship between individuals' attitudes, subjective norms and their investment intentions. Many studies have extended the traditional TPB model by incorporating variables from different perspectives. For instance, personality traits such as risk tolerance and uncertainty avoidance (Lim, Soutar, & Lee, 2013) are identified as antecedents predicting investment decisions. Cognitive factors, including financial literacy and investment experience, are recognized as strong predictors of investment intention (Raut, 2020). Moreover, social influences play a significant role in shaping investment behavior (Raut, 2020; Lai, 2019; Khawaja & Alharbi, 2021). These theories collectively highlight the importance of psychological, social and cognitive factors in understanding why individuals choose to invest in specific assets, including NFTs.

While six broad areas of determinants have been identified for investment intentions - (1) personal factors, (2) social factors, (3) market information, (4) firm-specific factors, (5) product-related factors and (6) demographical factors (Che Hassan *et al.*, 2023) – not all are directly applicable to NFTs. Firm-specific and product-related factors are less relevant to NFTs due to their lack of organizational backing. Instead, this study emphasized perceived value as a key determinant, reflecting the combination of aesthetic and financial evaluations that characterized NFTs (Ko *et al.*, 2022).

This study aims to investigate the influence of individuals' personal innovativeness, reward sensitivity and NFT knowledge – key personal factors – on their intention to invest in NFTs. Personal innovativeness captures an individual's willingness to adopt new technologies, while reward sensitivity highlights the anticipation of financial returns, both of them are particularly relevant to NFTs' speculative nature. NFT knowledge represents the cognitive aspect of investment, emphasizing the availability of market information in this emerging market.

In addition to personal factors, social influences, particularly subjective norms, are examined to understand how perceived social pressure affects individual's propensity to invest in NFTs (Perez *et al.*, 2023; Shanmugham & Ramya, 2012). The decision of an investor to invest in a specific product is influenced by various market, product and firm variables, including price fluctuations, relevant news, information from other sources and so on (Almansour, Elkrghli, & Almansour, 2023). This study will investigate the effects of the perceived risk of the traditional investing market and the perceived value of NFTs on investors.

Finally, this study examines the role of demographic and socioeconomic factors as moderating variables to capture their impact on investment behavior. Demographic characteristics play an influential role in shaping investment intentions. In this study, demographics are treated as moderating variables to examine their influence on the relationships between the key determinants and investment intentions. For example, younger investors may be more responsive to personal innovativeness, while older investors may place more emphasis on personal experience (Lai, 2019). Treating demographics as moderating variables would allow exploration of these interactions, providing deeper insights into the heterogeneous nature of NFT investment behaviors (Saivasan & Lokhande, 2022).

Personal innovativeness

Personal innovativeness refers to an individual's tendency to be the early adopter of novel products and experiences, which significantly influence their willingness to adopt new technological products (Hong, Lin, & Hsieh, 2017). For example, personal innovativeness is positively associated with the adoption of health and fitness applications (Acikgoz, Filieri, & Yan, 2023) and augmented reality as a shopping tool (Romano, Sands, & Pallant, 2022). Akhtar and Das (2019) also suggested that individuals with an intense disposition towards innovation are more likely to invest in the financial markets. NFTs, being digital assets, represent a novel concept in the domains of art, collectibles and digital ownership (Wilson

et al., 2022). Individuals with high personal innovativeness, who are willing to explore and embrace new concepts, are thus more willing to invest in NFTs (Sestino *et al.*, 2022). Therefore, we formulated the hypothesis that:

H1. Personal innovativeness is positively related to an individual's investment intention of NFTs.

Reward sensitivity

Reward sensitivity is defined as the extent to which behavior, emotion and cognitive processes are influenced by rewarding stimuli, such as food, social recognition or access to resources (Kim, Yoon, Kim, & Hamann, 2015). Individuals with high reward sensitivity often engage in goal-directed behavior to achieve positive outcomes (Carver, Sutton, & Scheier, 2000). Reward sensitivity is used to explain various human behaviors related to motivation, learning and emotion (Ávila, Parcet, & BarróS-Loscertales, 2008; Corr, 2004). It is also closely related to positive affectivity, approach motivation, extraversion, impulsivity, risk-taking and sensation seeking (Carver *et al.*, 2000; Elliot & Thrash, 2002; Satchell, Bacon, Firth, & Corr, 2018). Sun, Dedahanov, Shin, and Kim (2020) applied reward sensitivity to predict investors' intentions to switch their investments to the cryptocurrency market. In the context of NFTs, investors who exhibit greater sensitive to the returns and benefits of investing in NFTs are more likely to invest in them. Therefore, we hypothesize that:

H2. Reward sensitivity is positively related to an individual's investment intention of NFTs.

NFT knowledge

NFT knowledge refers to an individual's understanding of NFTs and their underlying blockchain technology. Several research studies have shown that possessing relevant financial knowledge is a reliable indicator of one's intention to utilize financial products and services (Akhtar & Das, 2019; Arora & Chakraborty, 2023; Lusardi & Mitchell, 2013). Hastings, Madrian, and Skimmyhorn (2013) found that financial knowledge positively influences decisions about credit card usage and investing tools. Similarly, research has shown that having information about products has a substantial impact on online purchasing behaviors (Karimi, Papamichail, & Holland, 2015). In the context of NFTs, knowledge plays a key role in empowering investors to invest these innovative financial products (Arora & Chakraborty, 2023). Consequently, the following hypothesis is proposed:

H3. NFT knowledge is positively related to an individual's investment intention of NFTs.

Subjective norms

Subjective norm refers to "the perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991, p. 188). Subjective norms, which are a form of social influence, are widely used to predict behavioral intentions, including consumers' mobile banking acceptance (Elhajjar & Ouaida, 2020), employees' investment of remote working (Odat, Alshurafat, Al Shbail, Ananzeh, & Al Amosh, 2023) and consumers' purchase of green products (Kumar & Pandey, 2023). Some studies also highlight the fact that subjective norms are significant determinants of investors' intention to invest in particular investment products (Alleyne & Broome, 2011; Pilatin & Dilek, 2023). For NFTs, subjective norms reflect the potential influence of social circles on an individual's decision to invest. As such, the following hypothesis is proposed:

H4. Subjective norms have a positive relationship with an individuals' intention to invest NFTs.

Perceived value of NFTs

Perceived value plays a key role in investment decisions by weighing monetary costs (transaction costs, relational costs, etc.) against nonmonetary considerations (time, effort, risk). Mattsson (1992) categorized value into three dimensions: emotional (consumer feelings), practical (functional and physical consumption) and logical (rational purchase). While originally a consumer decision-making construct, perceived value also applies to investment decisions, particularly in emerging technologies (Pham & Ho, 2015). For example, people's intention to adopt blockchain technology are influenced by their perceived usefulness and enjoyment (Grover, Kar, Janssen, & Ilavarasan, 2019). If individuals believe that blockchain can provide greater perceived value, it could potentially enhance their desire to utilize it (Yilmaz, Sagfossen, & Velasco, 2023). While cryptocurrencies lack inherent value, the perspective of investors regarding potential high returns plays a significant role in identifying instances of increased predictability in returns (Cheah & Fry, 2015).

In the context of blockchain and NFTs, perceived value often includes an assessment of potential returns and utility. Many customers acquire cryptocurrencies only for speculative purposes, aiming to capitalize on the substantial price fluctuations and retain them until the exchange rates appreciate (Böhme, Christin, Edelman, & Moore, 2015). However, some studies suggested that perceived usefulness and ease of use is a significant factor driving its investment (Mendoza-Tello, Mora, Pujol-López, & Lytras, 2018; Shahzad, Bouri, Roubaud, Kristoufek, & Lucey, 2019). Similarly, Yilmaz *et al*. (2023) and Sukumaran, Bee, and Wasiuzzaman (2022) also highlighted that perceived value is an important driver in NFT purchasing decisions. Thus, we hypothesize that:

H5. Perceived value of NFTs is positively related to a person's investment intention of NFTs.

Perceived risks of traditional investments

Some researchers have analyzed the correlation between cryptocurrencies and traditional investments, such as stocks, but the results of these studies have been inconclusive. Baur, Dimpfl, and Kuck (2018) argue that Bitcoin exhibits unique time series characteristics when compared to other assets, such as gold and the US dollar. Similarly, Umar, Jareño, and González (2021) and Charfeddine, Benlagha, and Maouchi (2020) found minimal correlation between cryptocurrency and traditional investments. However, some research indicates the presence of spillover effects, where risks in traditional markets may impact cryptocurrency investments (Aharon & Demir, 2022; Wang, 2022; Zhang, Sun, & Ma, 2022). In the case of NFTs, Dowling (2022) and Ko *et al*. (2022) found that NFTs exhibit low correlation with other assets, making them as effective tools for investment diversification and risk hedging. Investors who perceive traditional financial market as overly volatile or lacking attractive opportunities may be drawn to NFTs as a alternative investment. Therefore, we propose the following hypothesis:

H6. Perceived risk of traditional investment is positively related to a person's investment intention of NFTs.

Demographical factors

Demographic and socioeconomic factors, such as age, gender, income and investment experience, plays a key role in shaping investment behavior. These factors influence an individual's access to resources, risk tolerance and openness to technological innovations. For instance, Lai (2019) found that gender moderates the relationship between subjective norms and attitude towards investing in stocks. Kaur and Kaushik (2016) argued that demographic variables, including age, gender, occupation, income and education, influenced the level of awareness among Indian investors regarding mutual funds.

Research in the technology adoption domain further highlights the role of demographics. For example, users with higher income and more experience exhibit a greater intention to adopt and use mobile banking and payment services (Chawla & Joshi, 2023). However, limited research has examined the impact of user characteristics on their willingness to invest in NFTs. Examining user demographics is essential for comprehending the distinct effects of different factors on the intention to invest in NFTs, which allows investment platforms to customize their marketing strategies, design different communication strategies and formulate different marketing campaigns (Chawla & Joshi, 2023; Lai, 2019). Thus, we propose that to examine the effects of these factors on users' intention to invest in NFTs:

H7a. Personal innovativeness affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

H7b. Reward sensitivity affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

H7c. Subjective norms affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

H7d. NFT Knowledge affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

H7e. Perceived value affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

H7f. Perceived risk of conventional investment affects users' intention to invest NFTs differently based on (a) age, (b) gender, (c) income and (d) investment experience.

Research methodology

This study examines the determinants of NFT investment intentions of participants from Hong Kong and China. These regions represent significant markets for digital assets, characterized by a tech-savvy population with evolving interest in blockchain technologies. While the findings are based on participants in Hong Kong and China, the framework has broader applicability to other regions with similar technological ecosystems and market characteristics. Future research could extend this to compare findings across diverse cultural and regulatory environments, enhancing the generalizability of the model.

Participant and data collection

The data for this study was collected using online survey platforms, specifically Google Form and Wenjuanxing, through snowball sampling. In order to ascertain the participants' foundational understanding of NFTs, screening questions were implemented to verify that the respondents possess rudimentary knowledge regarding NFTs. The data was collected from May to June 2023. A total of 272 responses were obtained in this survey, all of which were complete and suitable for analysis (response rate 76.1%). Table 1 displays the demographic characteristics of the respondents. The largest demographic proportion consisted of males (51.1%) aged 31 to 40, holding an undergraduate degree and possessing 1–5 years of investment experience.

Measurement items

The measurement items utilized in this study were derived from previously validated instruments and were slightly adjusted to suit the specific context of this research (Table 1).

Table 1. Respondent profile

Respondent characteristics (N-272)	Frequency	Percentages (%)
Gender		
Male	139	51.10
Female	133	48.90
Age		
18–30 years old	108	39.70
31–40 years old	134	49.30
41–50 years old	28	10.30
50 years old or over	2	0.70
Education		
Primary education	2	0.74
Secondary education	34	12.50
Post-secondary/university education	190	69.90
Postgraduate education or above	46	16.90
Monthly income (in HKD)		
<15,000 HKD	65	23.90
15,001–30,000 HKD	134	49.30
30,001–45,000 HKD	56	20.60
45,001–60,000 HKD	13	4.80
>60,000 HKD	4	1.50
Investing experience		
<1 year	77	28.30
1–5 years	104	38.20
6–10 years	67	24.60
>10 years	24	8.80

Source(s): Authors' own work

The measurement of all constructs was conducted using multi-item scales. The participants were presented with a series of statements and were asked to rate their level of agreement on a seven-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Data analysis

The relationships in our model were examined using partial least square structural equation modeling (PLS-SEM) through the utilization of SmartPLS 4.08 software. PLS-SEM has garnered support from various disciplines within the social sciences, such as information systems research (Chin *et al.*, 2020), organizational studies (Ringle, Sarstedt, Mitchell, & Gudergan, 2020) and marketing (Sarstedt *et al.*, 2022). We employed PLS-SEM due to its capability to assess the impact of the construct on investment intention, as well as its support for estimating measurement models and intricate structural models (Hair, Hult, Ringle, & Sarstedt, 2016).

Result and findings

Exploratory factor analysis

An initial exploratory factor analysis (EFA) was performed to assess the 25 items on measuring different constructs. EFA helps identify latent constructs and their underlying factor structure (Fabrigar, Wegener, MacCallum, & Strahan, 1999). The analysis was conducted using VARIMAX rotation in SPSS 26. The resulting solution consisted of seven factors, which accounted for 72.4% of the variance. The Kaiser-Meyer-Olkin (KMO) test yielded a value of

0.896, which suggests that the sampling is sufficient. The Bartlett's test for sphericity yielded a result of 2917.22 ($p < 0.001$), indicating that the data is suitable for factor analysis.

Assessment of measurement models

According to Gefen, Rigdon, and Straub (2011) validation guidelines, it is necessary to test the reflective measurement model for its unidimensionality. According to Table 2, all items demonstrated acceptable levels as defined by Henseler, Hubona, and Ray (2016). Reliability was confirmed using Cronbach's alpha, with values ranging from 0.754 to 0.904, exceeding the acceptable threshold. Convergent validity was established through standardized factor loadings (all >0.7) and average variance extracted (AVE) values (range: 0.619–0.771), satisfying criteria proposed by Hair, Risher, Sarstedt, and Ringle (2019) and Fornell and Larcker (1981). Composite reliability (CR) for all constructs ranged from 0.754 to 0.905, further supporting convergent reliability (Hair *et al.*, 2019).

Next, discriminant validity was evaluated using the square roots of AVE values and heterotrait-monotrait (HTMT) ratios (Table 3). The square roots of the AVE values consistently exceeded the off-diagonal correlations, while HTMT values remained below 0.9, confirming adequate discriminant validity Henseler, Ringle, and Sarstedt (2015). Therefore, the overall reliability and validity of constructs were significant enough to perform the structural analysis using SEM for testing the proposed hypotheses.

Assessment of structural model

The structural model and hypotheses were assessed according to the processes proposed by Hair *et al.* (2016). Variance inflation factor (VIF) of NK, PR, PV, PI, RS and SN as predictors of IN ranged from 1.295 to 1.924, indicating no multicollinearity issues (Hair *et al.*, 2016). The coefficient of determination (R^2) of investment intention of NFTs was 0.566, demonstrating strong-to-moderate predictive power (Hair *et al.*, 2016; Henseler, Ringle, & Sinkovics, 2009).

After the bootstrapping procedure (5,000 samples, no sign changes option), 5 out of 6 structural relationships were significant ($p < 0.01$). The supported paths for investment intention (IN) were those with PI (H1), RS (H2), NK (H3), SN (H4) and PV (H5). In addition, the effect size (f^2) ranged from 0.036 to 0.097, indicating small-to-moderate predictive relevance (Hair, Sarstedt, Ringle, & Mena, 2012). The results are shown in Table 4 and Figure 1.

Personal innovativeness (H1), reward sensitivity (H2), NFT knowledge (H3), subjective norms (H4) and perceived value (H5) were all positively and significantly related to investment intention in NFTs. Specifically, the standardized path coefficients were as follows: personal innovativeness ($\beta = 0.321$, $p < 0.01$), reward sensitivity ($\beta = 0.284$, $p < 0.01$), NFT knowledge ($\beta = 0.301$, $p < 0.01$), subjective norms ($\beta = 0.256$, $p < 0.01$) and perceived value ($\beta = 0.347$, $p < 0.01$). These results provide strong support for the hypothesized relationships, indicating that these factors play critical roles in shaping NFT investment intentions. However, perceived risk of traditional investments (H6) demonstrated a weaker, albeit statistically significant, positive relationship with NFT investment intentions ($\beta = 0.182$, $p < 0.05$). While this supports H6, the smaller effect size suggests that perceived risk operates more subtly compared to the other predictors.

Multigroup comparison

To test hypotheses 7(a) to (f), four multi-group analyses were respectively conducted for age, gender, income and investment experience using the PLS-MGA approach proposed by Keil *et al.* (2000). Results indicated no significant differences for gender or investment experiences. However, significant group differences were observed for income and age: (1) a significant path was identified between subjective norm and investment intention across age groups and (2) a significant path was found between perceived value and investment intention across income groups (see Table 5).

Table 2. Quality criteria of the constructs

Constructs and items	Mean	SD	Standardized loading
Perceived risk (Sun et al., 2020) (CA = 0.852, CR = 0.863, AVE = 0.771)			
PR1 It is inconvenient to find good investment targets in the traditional financial market	3.628	0.802	0.880
PR2 It is not wise to spend a lot of time investing in traditional financial market	3.671	0.897	0.909
PR3 It costs too much to get satisfying expected returns on the traditional financial market	3.749	0.797	0.844
Reward sensitivity (Sun et al., 2020) (CA = 0.804, CR = 0.825, AVE = 0.718)			
RS1 A good opportunity to get profits from NFTs can motivate me to purchase or invest in it	3.541	0.708	0.810
RS2 In most cases, I prefer to do something that pays off soon	3.826	0.689	0.839
RS3 I want to be the best of the people around me	3.763	0.793	0.891
NFT knowledge (Chang & Chen, 2022) (CA = 0.845, CR = 0.849, AVE = 0.619)			
NF1 I know the function and purpose of the NFTs	3.696	0.730	0.788
NF2 I will learn voluntarily about the product knowledge of the NFTs	3.556	0.792	0.742
NF3 I can provide knowledge about the NFTs to other people	3.333	0.881	0.863
NF4 I have had the experience of learning the NFTs	3.691	0.751	0.813
NF5 I have had the experience of experimenting with the NFTs	3.164	0.991	0.719
Perceived value (Sukumaran et al., 2022) (CA = 0.863, CR = 0.865, AVE = 0.647)			
PV1 Using NFTs in investment could help me improve the effectiveness, profitability and investment of my wealth	3.609	0.715	0.798
PV2 I find that investing in NFTs can earn money as it allows me to invest it quickly and inexpensively with lower transaction costs	3.386	0.741	0.783
PV3 Using NFTs could help me improve my financial performance because I could have total control over my money	3.401	0.736	0.842
PV4 I feel satisfied with my NFTs investment decisions	3.691	0.738	0.785
PV5 Investing in NFTs will increase opportunities to achieve important goals for me	3.643	0.768	0.811
Personal innovativeness (San Martín & Herrero, 2012) (CA = 0.839, CR = 0.854, AVE = 0.755)			
PI1 I like to try new things	4.000	0.646	0.855
PI2 I like to try out the new things	4.072	0.703	0.874
PI3 If there is any new products for investment, I would look for ways to experiment with it	3.826	0.762	0.878
Subjective Norm (Armitage & Conner, 1999) (CA = 0.743, CR = 0.754, AVE = 0.660)			
SN1 People who are important to me thinks that I should invest in NFTs	3.188	0.749	0.843
SN2 My interaction with people influences me to purchase or invest in NFTs	3.357	0.709	0.753
SN3 My acquaintances would approve of my decisions to purchase or invest in NFTs	3.261	0.696	0.838
Investment intention (Sun et al., 2020) (CA = 0.904, CR = 0.905, AVE = 0.839)			
IN1 I am likely to purchase or invest in NFTs	3.652	0.714	0.914
IN2 I desire to purchase or invest in NFTs	3.430	0.815	0.908
IN3 I plan to purchase or invest in NFTs	3.633	0.813	0.927

Source(s): Authors' own work

Common method bias

As self-reported cross-sectional survey were used, common method bias (CMB) was tested by two statistical tests. The Harmon one-factor test revealed that a single factor accounted for only 37.91% of the variance, below the 50% threshold (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). A full collinearity test further indicated VIF values below the threshold of 5.0, confirming that CMB was not a serious concern in this study (Kock & Lynn, 2012).

Table 3. Discriminatory validity

Fornell-Larcker criterion correlation matrix

	NK	PI	PR	PV	RS	IN	SN
NK	0.787						
PI	0.504	0.869					
PR	0.338	0.233	0.878				
PV	0.609	0.467	0.355	0.804			
RS	0.500	0.364	0.501	0.475	0.847		
IN	0.595	0.524	0.399	0.588	0.584	0.916	
SN	0.388	0.393	0.172	0.399	0.271	0.470	0.813

Heterotrait-Monotrait ratio matrix

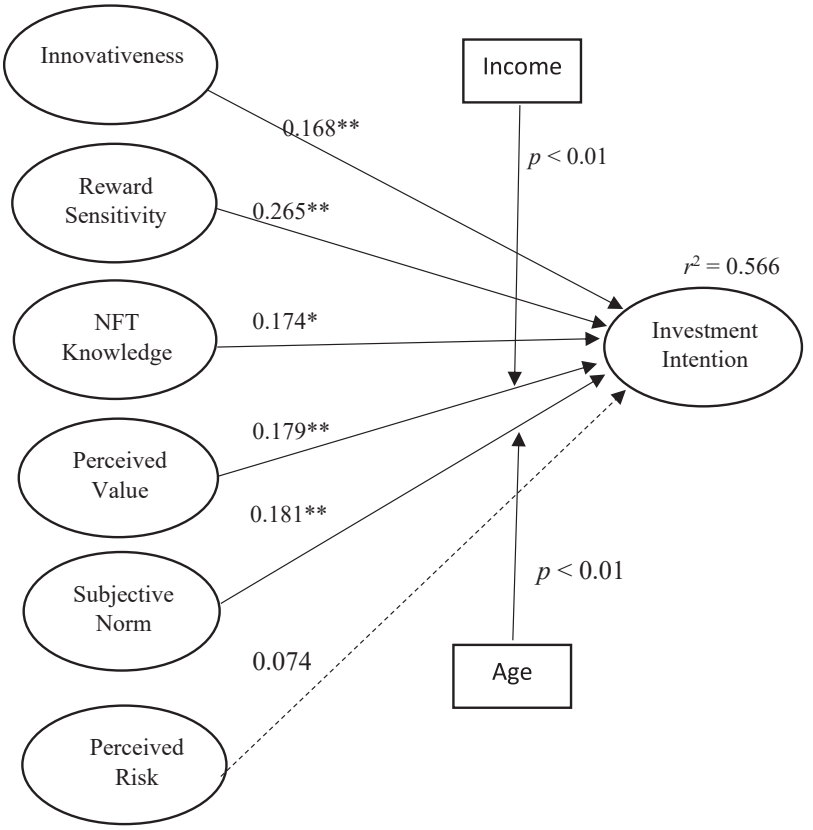
	NK	PI	PR	PV	RS	IN
NK						
PI	0.595					
PR	0.397	0.275				
PV	0.712	0.537	0.414			
RS	0.595	0.433	0.603	0.561		
IN	0.680	0.593	0.452	0.661	0.677	
SN	0.489	0.475	0.221	0.496	0.357	0.570

Source(s): Authors' own work

Table 4. Significance testing results of the structural model path coefficients

	Path	Std. Beta	SE	*t*-value	*p*-value	f-square	Result
H1	PI → IN	0.168	0.058	2.892	0.004	0.043	Supported
H2	RS → IN	0.265	0.074	3.591	0.000	0.097	Supported
H3	NK → IN	0.174	0.073	2.399	0.016	0.036	Supported
H4	SN → IN	0.181	0.060	3.008	0.003	0.058	Supported
H5	PV → IN	0.179	0.064	2.788	0.005	0.040	Supported
H6	PR → IN	0.074	0.056	1.308	0.191	0.009	Unsupported

Source(s): Authors' own work



Note(s): *$p^2 < 0.05$, **$p^2 < 0.01$
Source(s): Authors' own work

Figure 1. Result of structural model analysis

Discussion and implications

Results discussion

This study contributes to the existing literature by providing insights into the factors that influence users' intention to invest in NFTs. Our findings highlights the importance of personal factors, social influences and demographic characteristics in shaping investment intention.

Table 5. Comparison of age groups and income groups using PLS-MGA (H7a–H7f)

Path	Age group Gp 1: 108 respondents, ≤30 years old	Gp 2: 164 respondents, >30 years old	Gp1 vs 2 *p*-value	Income group Gp 1: 199 respondents, ≤HK$30,000	Gp 2: 73 respondents, >HK$30,000	Gp1 vs 2 *p*-value
PI → IN	0.265**	0.137*	0.266	0.201**	0.183	0.887
RS → IN	0.204*	0.287**	0.561	0.199*	0.464**	0.139
NK → IN	0.219*	0.218*	0.999	0.114	0.238	0.468
SN → IN	0.011	0.287**	*0.009*	0.123	0.325**	0.115
PV → IN	0.258*	0.086	0.248	0.313**	−0.099	*0.006*
PR → IN	0.024	0.073	0.654	0.091	−0.093	0.170

Note(s): Italic indicates a significant difference between Group 1 and Group 2 at a significance level
*$p < 0.05$, **$p < 0.01$
Source(s): Authors' own work

First, the significant role of personal innovativeness aligns with innovation diffusion theory, which asserts that early adopters are more open to novel technologies. Previous research on cryptocurrencies (Sun *et al.*, 2020) similarly emphasizes the importance of personal innovativeness. Our results suggest that individuals with high personal innovativeness are drawn to NFT for their unique features (Yilmaz *et al.*, 2023).

Second, the positive influence of reward sensitivity aligns with findings in behavioral finance, which associate reward-driven individuals with higher levels of risk-taking and speculative behavior (Satchell *et al.*, 2018). The anticipation of significant financial returns serves as a powerful motivator for NFT investments. This result aligns with theories of approach motivation (Carver *et al.*, 2000), which posits that the expectation of rewards drives decision-making, particularly in high-reward contexts like NFTs.

Third, consistent with cognitive models such as financial literacy frameworks (Lusardi & Mitchell, 2013), we find that knowledge about NFTs is a key driver of investment intentions. Knowledge enables investors to navigate the complexities of NFT trading with greater confidence (Sun *et al.*, 2020). Providing accurate and accessible information about NFTs may therefore enhance investment confidence and adoption rates.

The significant influence of subjective norms is supported by the Theory of Planned Behavior (Ajzen, 1991), which highlights the role of perceived social pressure in shaping behavioral intentions. Similar to findings in investment research (Lai, 2019; Sun *et al.*, 2020), our results suggest that opinions and behaviors within social networks influence individuals' decision regarding NFT investments.

The results also show how market and product factors relate to the investment intentions of NFTs. This finding is consistent with the study of purchase intention of NFTs conducted by Fortagne and Lis (2023), which indicate that the perceived value and utilitarian attitude toward NFT has strong influence on the purchase intention of NFTs. However, our finding that perceived traditional investment risk is not significantly related to NFT investment intention. This finding deviates from conventional investment market theories and raises intriguing questions about the unique nature of NFTs as an investment asset (Dowling, 2022). This deviation highlights the need for further research into the relationship between NFTs and conventional asset classes.

Finally, demographic factors, such as age and income, moderate the relationships between the identified determinants and investment intention. The results show that subjective norm is less influential for the younger group of investors to consider purchasing NFTs and the perceived value of NFTs is more emphasis by lower income group when they make their investment decision. These findings align with prior studies on demographic influences (Lai, 2019) and suggest that the impact of personal factors and social influences on investment intention may vary depending on individuals' demographic characteristics.

Theoretical implications

This study offers important theoretical contributions to the understanding of NFT investment behavior. By examining personal factors, social influences and the moderating effects of demographic factors, our research extends existing theories in behavioral finance and technology adoption. These findings contribute to both academic research and practical applications in the field of NFT investments and enrich the literature on emerging financial markets.

First, our study confirms that constructs traditionally applied to technology adoption and financial investments – such as personal innovativeness, knowledge and reward sensitivity – are also relevant in the contexts of NFTs. This supports the generalizability of these constructs across different asset types, including novel digital assets. Importantly, integrating perceived value into the model, our research highlights the dual finance and emotional appeals of NFTs, advancing theories on utilitarian and hedonic motivations in investment decisions.

Second, the non-significance of perceived risks challenges established assumptions in cryptocurrency literature that perceived risk perception as a key consideration of investment behavior (Wang, 2022; Zhang *et al.*, 2022). Our findings suggest that investors may perceive NFTs as distinct from cryptocurrencies, focusing more on their innovative and speculative nature rather than traditional risk evaluations. This contributes to the growing literature distinguishing NFTs from broader blockchain-based financial products.

Finally, the study enhances theoretical models such as the Theory of Planned Behavior (Ajzen, 1991) by incorporating demographic moderators. Findings that younger investors are less influenced by subjective norms and that lower-income investors place greater emphasis on perceived value highlight the heterogeneous nature of NFT investment behavior. These insights extend existing theories by illustrating how individual differences shape decision-making in the context of emerging financial markets.

Managerial implications

Overall, this timely study delivers valuable theoretical and practical insights into an emerging investment domain. By identifying key drivers of NFT investment intentions, the study informs strategies to attract investors, such as emphasizing financial rewards, improving knowledge, leveraging social influences and enhancing perceived value of NFTs as digital assets.

To use the connection between personal factors and investment intention of NFTs, it is beneficial to target on persons who possess a high level of personal innovativeness and reward sensitivity. People with high level of personal innovativeness are more likely to explore the unique and groundbreaking characteristics of NFTs. Engaging with tech enthusiasts, early adopters and influencers can foster a favorable view of NFTs and promote their acceptance across a broader demographic. As individuals who are sensitive to high returns and rewards are more likely to express an interest in investing in NFTs, it is important to emphasize the potential financial gains associated with NFT investments. Marketing campaigns and investment guides can highlight success stories and showcase the profitability of NFT investments. This can attract more investors who are motivated by the allure of significant financial gains.

Given the significant role of NFT knowledge in driving investment intention, it is crucial to provide individuals with sufficient information, skills and knowledge about NFTs and other cryptocurrencies. Workshops, seminars and training programs can be organized by universities, financial institutions and industry professionals to provide education to potential investors regarding the distinctive characteristics and advantages of NFTs. This can enhance self-assurance and motivate investors to incorporate NFTs into their financial portfolios.

Due to the impact of subjective norms on investment decisions, it is essential to cultivate favorable perceptions and opinions regarding investments in NFTs. One effective approach to achieve this is by utilizing social proof, which involves showcasing successful NFT investors and their experiences to influence the investment decisions of others. By establishing a

network of NFT investors and encouraging discussions, a supportive environment can be created that promotes investment in NFTs.

Recognizing the influence of perceived value of NFTs on investment intentions, it is crucial to focus on enhancing the perceived value and utility of NFTs as investment assets (Vishnu Prasad, Murthy, Joseph, & Adhikari, 2023). This can be achieved by promoting the uniqueness, scarcity and authenticity of NFTs (Fortagne & Lis, 2023). Additionally, conducting further research to understand the relationship between NFTs and traditional investment markets can provide valuable insights for investors and guide their decision-making process.

Limitation and future studies

The present study serves as a valuable starting point for understanding the relationship between various factors and the investment intention of NFTs. While this study provides insightful findings, there are certain limitations that hinder drawing conclusive results. Firstly, the study was conducted with investors in Hong Kong and China using a non-probabilistic sampling method. Therefore, caution is advised when generalizing and applying the results to other populations. Future research should aim to include investors from diverse cultures and demographic backgrounds.

Secondly, it is important to acknowledge that there are different types of NFTs, and investors in each type may have distinct expectations, values, motivations and behaviors. This study did not explore the key characteristics among various types of NFT investors. Given the rapid development of cryptocurrencies and NFTs, it is anticipated that more types of NFTs will emerge. Future studies can delve into the psychological processes and behavioral outcomes of investors across different types of NFTs and cryptocurrencies.

Lastly, in recent years, the platforms and processes involved in investing in NFTs and cryptocurrencies have become more comprehensive. There are multiple touchpoints throughout the investment process. For instance, key opinion leaders may promote new cryptocurrencies through various social media platforms during the pre-consumption stage. Following the promotion, they may encourage viewers to join social network groups to foster ongoing communication and relationships during the post-consumption stage. Future studies can expand their scope to include more communication and promotional elements across different stages of NFT investment. This will enable a better understanding of the unique characteristics of this rapidly evolving domain of cryptocurrencies and NFTs.

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