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RESEARCH ARTICLE

A survey of attitude and behavior of Indian equity investors towards cryptocurrencies: Using smart-PLS and systematic equation modeling (SEM) approach

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Abstract
There hasn't been much study done specifically addressing the attitudes and behaviors of the Indian equities market investors towards cryptocurrencies. The main goal of this investigation is to explore the attitude and behavior of the retail investors of the equity market towards cryptocurrencies with context to India. The study included 200 retail investors in the Indian equity market with snowball and convenience sampling methods. Smart-PLS and SPSS were applied to check the research hypothesis. The outcome revealed that investors are aware but a majority of the investor respondents still have no investment experience in cryptocurrency. Further, the research showed the impact of perceived ease of use (EU) and perceived benefits (PB) on both investors' attitudes as well as their behavioral intention towards cryptocurrency investments. Vulnerability didn't have a significant impact on attitudes but did affect behavioral intentions, which indicates the importance of addressing perceived risks to foster cryptocurrency investment. To enhance cryptocurrency adoption, platforms are required to prioritize the ease of use, clear communication of benefits and strategies to mitigate the investor's concerns about risk. This study offers new perspectives to aid financial institutions, government regulatory bodies and future researchers in comprehending the changing scenario of equity investors' behavior and attitudes regarding cryptocurrencies in India.

Keywords: Attitudes, Behaviors, India, Cryptocurrencies, Equity market, Investors, Smart-PLS.

Introduction

Technology adoption has become a major and prime factor in human development (Patwardhan, 2018). Throughout time, advancements in technology such as digital payments, e-commerce and the Internet of Things (Rüßmann *et al*., 2015) have given rise to what we now recognize as virtual currencies known as «cryptocurrencies.» In recent years, cryptocurrencies have solidified their position as a fresh alternative investment category and have become more popular with online investors worldwide (Colombo & Yarovaya, 2024). Although these cryptocurrencies are considered risky due to their instability prices, the number of investors investing in cryptocurrencies is still on the rise (Wasiuzzaman & Hj, 2024). In India, cryptocurrencies are neither issued, guaranteed, nor backed by central banks or monetary authorities (Arli *et al*., 2021) for use as a medium of payment.

Despite being the most volatile and risky investment (Ben & Xiaoqiong, 2019; Sun *et al*., 2021) compared to traditional asset classes such as commodities, stocks and bonds (Subramaniam & Chakraborty, 2020) cryptocurrency market has shown remarkable expansion ever since Bitcoin was introduced in 2009. From 2012 to 2021, the market value of cryptocurrencies has increased from around \$500 million to \$782.0 billion, with an annual growth rate of 150%. (Sun *et al*., 2021). Despite the possibility of danger and uncertainty, 2020 and 2021 were important for accepting cryptocurrencies (Bruhn & Ernst, 2022).

Even though individual investors are the main users of crypto assets, institutional investors have also started using

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them recently (Pilatin & Dilek, 2024). Numerous studies have been carried out examining different aspects such as risks (Li, 2024; Ferreira *et al*., 2024; Angerer *et al*., 2021; Enoksen *et al*., 2020), volatility (Bruzgė *et al*., 2023; Siu, 2021), speculative nature (Tan *et al*., 2020), return and volatility (Koutmos, 2018), uncertainty in regulations (Sauce, 2022; Raza *et al*., 2023; AlShboul *et al*., 2023), blockchain and its implementation (Abou Jaoude & Saade, 2019;

Akhtar *et al*., 2019; Bailis, 2017) and so forth. This significant increase has spurred the need for this study, as the investor base is expanding and varying. It is essential to grasp the changing investment perspective of investors in this volatile market to prevent harm to investors. Although there are many researches on the influence of retail investors' abilities, experience, and knowledge on their investment decisions involving risk (Agarwal & Mazumder, 2013; Bellofatto *et al*., 2018), limited studies are focusing on the attitudes and behaviors of investors towards cryptocurrencies in India. This study was undertaken by considering this research gap.

The objective of this empirical study is to analyze the attitudes and behaviors of equity investors in India towards cryptocurrencies, which are emerging as a new trend in the financial and economic landscape. The structure of this study contains the following sections. In chapter 2, a related literature and research hypothesis are developed. Chapter 3 presents the data methodology used to investigate attitudes and behaviors towards cryptocurrencies in India. Part 4 presents the analysis & interpretation of the collected data. The next section shows the conclusion and managerial implications along with the constraints of this study.

Cryptocurrencies in India

Cryptocurrency has become a burning topic in India, drawing the interest of investors, academics and researchers. Nevertheless, the vague position of the Indian government on cryptocurrencies is confusing potential investors and businesses. Since the beginning, RBI has consistently warned investors about the potential risks of cryptocurrencies. In 2018, the Reserve Bank of India circulated a notice prohibiting financial and banking institutions from dealing with cryptocurrencies, which had the effect of significantly lowering the volume of cryptocurrency trading in India and closing a number of exchanges and businesses.

But in March 2020, the Supreme Court of India declared the RBI's circular invalid, deeming it unconstitutional. This action sparked a fresh enthusiasm for cryptocurrencies in India, leading to the reopening of numerous cryptocurrency exchanges. As per the Global Crypto Adoption Index 2024, India has secured the top rank in global cryptocurrency adoption (Chainalysis, 2024). This scenario reflects India's emerging position as one of the leading countries in cryptocurrency adoption, despite the continuous oppose from the RBI and lack of government support.

Fred davis' Technology Adoption Model (TAM) and Hypothesis Development

There are numerous popular theories to understand the people's perception behind the adoption of new ideas and technology. The TAM is one of those theories that explain how individuals adopt new technologies (Venkatesh & Davis, 2000). It is recognized as one of the most significant developments of Ajzen and Fishbein's TRA theory in academic literature (Davis, 1989). Due to TAM's extensive scope and its relevance to different situations, researchers argue that it offers a useful structure for investigating attitudes and behavior. TAM suggests that the perceived usefulness (PU) and ease of use (EU) of technology affect the users' intention to adopt it (Davis *et al*., 1989). The following section presents several empirical studies and hypotheses:

Attitude Toward Cryptocurrency

The prior studies indicated a weak connection between attitude and behavior towards cryptocurrency adoption (Albayati *et al*., 2020) (Brown, 1980). However, numerous academics debated this theory, pointing out methodological errors. Hence, Ajzen and Fishbein conducted a study to re-evaluate the theoretical bases to comprehend behaviors linked to attitudes and found strong correlations between attitudes and behaviors globally (Fishbein, 2005). Attitude is how someone feels about an object or concept in a situation, whether it is positive or negative (Ajzen, 1980). An individual's intention to adopt technology can be directly impacted by their attitude (Taylor & Todd, 1995). Several types of studies revealed that attitude has a substantial effect on behavioral intention towards financial decisions (Ali, 2011; Adam & Shauki, 2014; (Raut & Das, 2017). Therefore, the following hypotheses are as follows:

$H1_0$ Attitude and behavioral intention for cryptocurrency investment are uncorrelated.

$H1_1$ Attitude and behavioral intention for cryptocurrency investment are correlated.

Perceived Benefit

The term «perceived benefit» describes both functional and non-functional benefits that consumers feel when they purchase goods or services (Kyguoliene *et al*., 2017). While non-functional benefits are linked to emotions, such as a pleasurable and fascinating shopping experience, functional benefits relate to utilitarian functions that are associated with functional benefits, for example, convenience, variety, and quality (Forsythe *et al*., 2006). In another study, perceived value was employed to determine ROI (return on investment) and efficiency. It has to do with understanding how retail investors see the benefits of making cryptocurrency investments. (Sukumaran *et al*., 2023). Users' attitudes towards a particular technology are greatly influenced by its perceived usefulness, which in turn greatly influences their investment intentions to adopt it

(Taylor & Todd, 1995); (Liu & Prybutok, 2021). Perceived utility (PU) was categorized as an attitude-determining element in the expectation-disconfirmation theory of technology adoption (Taylor & Todd, 1995). Thus, the following hypothesis is framed:

$H2_0$ Perceived benefit and attitude towards cryptocurrency investment are uncorrelated

$H2_1$ Perceived benefit and attitude towards cryptocurrency investment are correlated.

$H3_0$ Perceived benefit and behavioral intention for cryptocurrency investment are uncorrelated.

$H3_1$ Perceived benefit and behavioral intention for cryptocurrency investment are correlated.

Vulnerability or Perceived Risk

Perceived risk is a person's beliefs and expectations regarding the harm or loss that may occur as a result of a particular scenario or combination of circumstances. This belief can greatly impact the decision-making process. When an individual's risk exceeds their tolerance threshold, it can adversely affect their purchasing intention of products or services (Venkatesh & Goyal, 2010). However, perceived risk is also affected by cultural background and personal experiences (Keil *et al*., 2000). Additionally, perceived risk can also play a role in an individual's willingness to disclose personal information online, further impacting their behavioral intentions (Dinev & Hart, 2006). Hence, the following hypothesis is framed:

$H4_0$ Attitude and vulnerability towards cryptocurrency investment are uncorrelated.

$H4_1$ Attitude and vulnerability towards cryptocurrency investment are correlated.

$H5_0$ Behavioral intention and vulnerability towards cryptocurrency investment are uncorrelated.

$H5_1$ Behavioral intention and vulnerability towards cryptocurrency investment are correlated.

Perceived Ease of Use

The degree to which an individual perceives that a specific system or technology is simple to understand and use is known as perceived ease of use (Teo *et al*., 1999). Technology acceptance model (TAM) states that perceived usefulness (PU) and perceived ease of use (EU) are the two factors that influence a technology adoption decision (Davis *et al*., 1989)). The PU and EU form a user's beliefs and behavioral intentions that impact the outputs of technology (Ho *et al*., 2017) and may also directly influence the intention of accepting behavior (Taylor & Todd, 1995). EU has been recognized as a crucial factor in the adoption of digital banking technology (Celik, 2008). Furthermore, several other studies have found a positive association between the perceived ease of use and technology adoption intention (Al-Somali *et al*., 2009); (Bashir & Madhavaiah, 2015); (Yoon & Steege, 2013). Based on the reviewed literature, the following hypotheses are structured for this research:

$H6_0$ Perceived ease of use and attitude towards the cryptocurrency investment are uncorrelated.

$H6_1$ Perceived ease of use and attitude towards cryptocurrency investment are correlated.

$H7_0$ Perceived ease of use and behavioral intention for cryptocurrency investment are uncorrelated.

$H7_1$ Perceived ease of use and behavioral intention for cryptocurrency investment are correlated.

Behavioral Intention

Behavioral intention (BI) is a key determinant of customer behavior and is affected by various factors such as attitude (A), perceived behavioral control (PBC), and subjective norms (SN) (Taufique & Vaithianathan, 2018). A more positive attitude leads to a high tendency to take a particular action, as evidenced by the relationship between individual investors' attitudes and behavioral intentions while making investment decisions (Mandell & Klein, 2007; Borden *et al*., 2008). (Phan & Zhou, 2014; Rahmani *et al*., 2023) also showed a significant and positive relationship between attitudes and behavioral intentions towards financial choices. (Phan & Zhou, 2014; Rahmani *et al*., 2023).

Material And Methods

Research Design and Survey Instrument

To understand the investors' perceptions and attitudes towards cryptocurrencies, a self-structured questionnaire was utilized to obtain data in conjunction with a quantitative research approach for the present study. TAM model was adapted for this research to assess the attitude and behavior of respondents towards cryptocurrency. Initially, we conducted a pilot study and gathered feedback from fifteen close contacts on the questionnaire. Based on their responses received, we made the modifications to the questionnaire. To ensure a timely response, broad reach and cost-effectiveness, an online survey using the Google Forms link was used to gather the data along with the face-to-face contacts. The questionnaire was comprised of two sections: the initial section gathered the sample's demographic information, including gender, age, educational background, investment experience, monthly income, occupation of the respondents, cryptocurrency awareness and their investment experience in cryptocurrencies. The second part of the questionnaire encompassed all the items/ statements of the constructs related to the TAM model. The questionnaire contained 22 questions, broken down into Perceived Benefit (6), Vulnerability (6), Ease of Use (3), Behavioral Intention (4) and Attitude (3). Some items were eliminated from the model due to insufficient validity. The second section included questions about the type of investor, familiarity with cryptocurrency and sources of awareness. The research questionnaire initially had 28 items, but after screening, 22 items remained. With the exception of demographic information, each item was rated using a five-point Likert scale ranging from «strongly disagree» (1) to «strongly agree» (5). Binary variables 0 and 1 were given to «no» and «yes» respectively. By following these procedures, the data was ensured accurately and effectively in SPSS.

Data Collection and Sample Size

The basic requirement of the sampling design was to include the Indian stock market investors within the population for this study. This research applied the cross-sectional approach to get responses to attain the hypothesized goals. This study employed non-probability sampling techniques (snowball and convenience sampling methods) to collect primary data. For this, self-designed closed-ended questions were designed on a 5-point scale. The data was collected between January 2023 and July 2024. Respondents were informed of the objective of the investigation and assured that their responses would be kept confidential and used for educational purposes only. A total of 264 questionnaires were obtained via the Google form link and a further 50 questionnaires were received via direct contacts. Out of these 200 deemed legitimate questionnaires were used for the survey after cleaning and reviewing the inconsistencies in the questionnaire, such as missing data or filter questions. For analyzing the data, AMOS-18, Smart PLS and SPSS-25 were used.

Data Analysis Techniques

Statistical model estimation is a forecasting technique that aims to optimize the explained variance (Hair *et al*., 2019). To access the impact of various constructs on equity investors' attitudes and behaviors towards cryptocurrencies in India, AMOS 18 and PLS-SEM were applied. At the initial stage of analysis after data collection, SPSS-25 was primarily employed to check reliability and validity with a significance level of 0.05. Additionally, exploratory factor analysis (EFA) was conducted prior to path analysis using PLS-SEM to ensure the authentication of the survey scale and data.

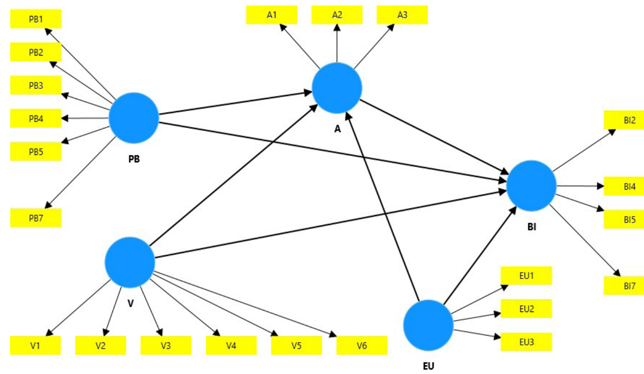
Model Structure and Constructs

In the model (Figure 1), attitude and behavioral intention were the endogenous variables, and exogenous variables were perceived benefit, perceived ease of use, and vulnerability for this study. The correlation among them was measured by using a uni-directional causal relationship. All variables were measured using items/statements with a five-point Likert scale and were adopted from the various literature. The model formulation is presented below (Safari *et al*., 2022):

$$ATT = TAM\ \beta_i + e_i$$
$$INT = TAM\ \beta_{1i} + ATT\beta_{2i} + e_i$$

Results

In the preliminary phase, the characteristics of the participants and the research results were obtained using SPSS and Smart PLS, which are shown in this section.



Source: Author's work

Figure 1: Research model

Sample Profile Descriptive Analysis: Sample Profile

Table 1 shows the participants' demographic profile. In this study, 200 valid participants were identified after screening which includes 131 (65.5%) male and 69 (34.5%) female respondents. Evidently, the majority of participants were male over female. Most of the participants in the sample were between 15 and 25 years old, there were only a few investors (5.5%) over 45 years old. This indicates the younger generation is very interested and enthusiastic towards the stock market. Furthermore, major participants (58%) were graduates and only 19% of the respondents were undergraduates. In terms of occupation, it is clearly visible that 47.5% of the respondents were salaried, 31% of the participants were self-employed and 7.5% of the surveyed participants were housewives. Regarding income, the monthly income of 38% of the respondents was less than ₹1 lakh per month, while 23.5% earned between ₹1 and ₹3 lakh and 20% earned between ₹3 and ₹6 lakh. In the profile of investment experience, 39.5% had 1-2 years of experience, and 32% had less than 1 year. It can be seen that 87.5% of participants were aware of cryptocurrency, out of which only 46% had actual investment experience. The frequency and statistical tables for the sample were calculated using SPSS 25 statistical software. From the analysis of the Table 1, a conclusion can be inferred that a major proportion of investors are aware of cryptocurrency but hesitate in cryptocurrency investment. Furthermore, the data were analyzed and the hypotheses were tested using AMOS and PLS-SEM with variance. This enabled the investigation of interconnected dependency relationships between variables (Sarstedt *et al*., 2016). The maximum likelihood estimation (MLE) regression technique was chosen for this study as it is one of the recommended techniques for measuring designs, estimating structural models and performing goodness-of-fit tests (Henseler *et al*., 2016). The smart-PLS software was used for calculation and analysis as it is more suitable for predicting and investigating

Table 1: Respondents' demographic profile (n = 200)

S. No.	*Respondents' profile*	*Category*	*N*	*%*
1.	Gender	Male	131	65.5
		Female	69	34.5
2.	Age	15–25 years	87	43.5
		26–35 years	76	38.0
		36–45 years	26	13.0
		Above 45 years	11	5.5
3.	Qualification Background	Undergraduate	38	19.0
		Graduate	116	58.0
		M.Phil./Ph.D.	13	6.5
		Others	33	16.5
4.	Occupation	Self-employed	62	31.0
		Salaried	95	47.5
		Housewife	15	7.5
		Retired	3	1.5
		Others	25	12.5
5.	Monthly Income	Below 1 Lacs	76	38
		1–3 Lacs	47	23.5
		3–6 Lacs	40	20.0
		Above 6 Lacs	37	18.5
6.	Investment Experience	Below 1 year	64	32.0
		1–2 years	79	39.5
		2–5 years	31	15.5
		Above 5 years	26	13.0
7.	Cryptocurrency Awareness	Yes	175	87.5
		No	25	12.5
8.	Crypto-investment Experience	Yes	92	46.0
		No	108	54.0

relatively new phenomena (Chin, 1999). This approach was appropriate for the current study as it has a small sample size of 200 participants and Smart-PLS often provides the appropriate results in a small sample size of observations (Reinartz *et al*., 2009).

Measurement Model Assessment: Reliability, Convergent Validity

Reliability refers to the consistency shown in consecutive measurements (Carmines, 1979). It evaluates how well study findings can be repeated in identical circumstances. Cronbach's alpha is regarded as the most reliable and valid form of reliability analysis when evaluating the dependability of a set of items. This value is between 0 and 1, with a threshold of 0.7 to 0.9 being regarded as acceptable to very good (Cronbach, 1951). After removing six statements with values less than 0.7 (Tables 2 and 3), the study's results showed 0.951 Cronbach's alpha value of 22 items (Table 1).

Table 2: KMO and Bartlett's test

Kaiser-Meyer-Olkin measure of sampling adequacy	.951
Bartlett's test of Approx. Chi-sphericity Square	2482.7 58
df	231
Sig.	.000

Regression Assumptions

Table 4's collinearity statistics (Tolerance and VIF) indicate that multicollinearity is not a cause of concern. As evidence that the predictors don't overly overlap in explaining the result, all VIF values are below 10, and tolerance values are

Table 3: Factor loading before removing the statements

	Outer loadings
A1 <- Attitude	0.797
A2 <- Attitude	0.832
A <- Attitude	0.831
BI1 <- Behavioral intention	0.638**
BI2 <- Behavioral intention	0.752
BI3 <- Behavioral intention	0.654**
BI4 <- Behavioral intention	0.762
BI5 <- Behavioral intention	0.778
BI6 <- Behavioral intention	0.675**
BI7 <- Behavioral intention	0.790
EU1 <- Perceived ease of use	0.842
EU2 <- Perceived ease of use	0.805
EU3 <- Perceived ease of use	0.862
EU4 <- Perceived ease of use	0.657**
PB1 <- Perceived benefit	0.786
PB2 <- Perceived benefit	0.707
PB3 <- Perceived benefit	0.792
PB4 <- Perceived benefit	0.788
PB5 <- Perceived benefit	0.722
PB6 <- Perceived benefit	0.671**
PB7 <- Perceived benefit	0.815
V1 <- Vulnerability	0.876
V2 <- Vulnerability	0.812
V3 <- Vulnerability	0.775
V4 <- Vulnerability	0.868
V5 <- Vulnerability	0.829
V6 <- Vulnerability	0.851

NOTE: **Removed values less than .7

above 0.1. Consequently, all predictors with *p-values* less than 0.05 are deemed statistically significant.

According to Table 5, the model can account for 68.4% of the variation observed in the dependent variable. The ANOVA Table 6 further supports the regression model's fit for the data. The high F-value (68.479) and low *p-value* (0.000) indicated that the model is statistically significant, meaning that the independent variables together explain a significant portion of the variance in Behavioral intention. Table 6 shows a linear dependent relationship between the independent and dependent variables.

Table 5: Model summary

Model	*R*	*R^2*	*Adjusted R^2*	*St. Error of Estimate*
	.827[a]	.684	.677	.47148

Predictors: (Constant), Attitude, Vulnerability, Ease of use, Perceived benefit

Table 6: ANOVA[a]

Sum of	*Mean*	*Squares*	*df*	*Square*	*F Sig.*
Regression	93.722	4	23.431	105.402	.000[b]
Residual	43.348	195	.222		
Total	137.070	199			

Dependent Variable: Behavioural Intention
Predictors: (Constant), Attitude, Ease of use, Perceived benefit, Vulnerability

Table 7: Model finding values

Measure	*Threshold*	*Model value*	*Decision*
Chi square/df (CMIN/DF)	<3 good;	1.117	Accepted
GFI	>.95	.913	In limit
AGFI	>.80	.890	Accepted
SRMR	<.90	.060	Accepted
RMSEA	<.05 good	.024	Accepted
PCLOSE	>.05	.998	Accepted
TLI	>.90	.989	Accepted
CFI	>.90	.920	Accepted

Assessment of Structural Model

To conduct CFA on the latent constructs, the measurement model was employed. According to (Murtagh & Heck, 2012), AMOS is frequently used to assess model fitness using a variety of indices, including RAMSEA, DFI, CFI and Chi-square/df. CMIN/df, i.e., the discrepancy divided by the degree of freedom, should ideally be ≤ 3 for an acceptable fit, ≤ 5 for an adequate fit and equal to 1 for a perfect fit. For a reasonable fit, the goodness of fit index should be ≥ 0.9

Table 4: Coefficients

Model		*Unstandardized coefficients*		*Standardized coefficients*	*t*	*Sig.*	*Collinearity statistics*	
		B	*Std. error*	*Beta*			*Tolerance*	*VIF*
1	(Constant)	.357	.144		2.472	.014		
	Perceived_benefit	.306	.069	.311	4.463	.000	.334	2.994
	Vulnerability	.162	.040	.199	4.022	.000	.661	1.512
	Ease_of_use	.237	.058	.250	4.065	.000	.428	2.339
	Attitude	.203	.061	.217	3.327	.001	.380	2.629

Dependent variable: Behavioral Intention

Table 8: Measurement model results

Constru ct along with statements	*External loading*	*CRA*	*CR*	*AVE*	*VIF*	*Mean value*	*SD*
Attitude (A)		0.757	0.860	0.673			
I believe that the cryptocurrency market will play a more significant role in the financial markets than equities in the future. (A1)	0.793				1.419	3.2000	1.15180
I believe that the cryptocurrency market will grow more in India compare d to the equity market. (A2)	0.835				1.610	3.3050	1.08065
As an investment option, the CC market has bright and long-term growth potential as compare d to the equity market. (A3)	0.833				1.597	3.2700	1.01600
Behavioral Intention (BI)		0.772	0.854	0.594			
I can use cryptocurrency for efficient monetary transactions rather than equities. (BI2)	0.765				1.404	3.3550	1.10229
I believe that I can use the CC to obtain better returns for investments than equities. (BI4)	0.777				1.534	3.1650	1.08335
I recommend cryptocurrencies as an investment option to others based on my experiences and perceptions. (BI5)	0.773				1.503	3.3450	1.03019
I have adequate payment options and methods available for buying and selling cryptocurrencies in India. (BI7)	0.765				1.596	3.0150	1.09121
Ease of Use (EU)		0.786	0.875	0.700			
The analysis in the CC market is easier rather than in the equity market. (EU1)	0.842				1.680	2.8850	1.07122
Transacti on in cryptocurrencies are easier compared to equity transactions. (EU2)	0.805				1.557	3.0600	.99567
Cryptocurrencies are easily transferable as compared to equities. (EU3)	0.862				1.718	2.8050	1.06897
Perceived Benefit (PB)		0.861	0.897	0.592			
Cryptocurrencies offer higher returns compared to equity investments. (PB1)	0.786				1.877	3.2000	1.06096
The high price fluctuations in the cryptocurrency market attract more investors as compare d to the equity market. (PB2)	0.707				1.556	2.9850	1.14074
I believe that investing in cryptocurrency is more	0.791				1.888	3.2450	1.06803

speculative than investing in equities. (PB3)							
I view cryptocurrency as a better diversification tool in an investment portfolio than equities. (PB4)	0.78 8				1.9 23	3.2 700	1.06 902
Cryptocurrencies are long-term investments compared to equities. (PB5)	0.72 1				1.6 38	3.1 450	1.05 810
I can make better purchase decisions with cryptocurrency. (PB7)	0.81 6				2.0 59	3.1 800	1.18 940
Vulnerability (V)		0.9 13	0.9 33	0.6 99			
The absence of a regulatory framework makes cryptocurrency riskier than equities. (V1)	0.87 1				3.0 44	3.2 800	1.25 278
Money laundering g, scams illegal activities etc. make it riskier than the equity market. (V2)	0.76 1				2.0 24	3.3 000	1.11 635
Lack of awareness and educatio n enhances the risk in the CC market as compare d to the equity market. (V3)	0.76 2				1.9 29	3.1 350	1.09 672
The possibility of sudden policy changes in India makes cryptocurrency riskier than other assets. (V4)	0.85 8				2.8 51	3.3 050	1.24 891
Taxes on cryptocurrencies are relatively very high as compared to equities. (V5)	0.78 0				2.3 65	3.5 000	1.27 992
Cryptocurrencies are less accessible rather than the equity market. (V6)	0.85 1				2.7 49	3.4 350	1.31 698

Notes: CRA for Cronbach's alpha, CR for composite reliability; AVE for average variance extracted; VIF for variance inflation factor
Source: Pls-SEM

Table 9: Fornell-Larcker criterion

	Attitude	*Behavioral intention*	*Perceived ease of use*	*Perceived benefit*	*Vulnerability*
Attitude	0.820				
Behavioral intention	0.720	0.771			
Perceived ease of use	0.700	0.700	0.837		
Perceived benefit	0.741	0.765	0.708	0.769	
Vulnerability	0.493	0.590	0.387	0.576	0.836

Note: Diagonals' value shows the square root of the AVE =, while the off diagonals show the correlation.

Table 10: Hypothesis results: path coefficient and statistical significance

Hypothesis	*Hypothe sized path*	*Original sample (O)*	*Saple mean (M)*	*Standard deviation (STDEV)*	*T-value*	*Path coefficient*	*F2*	*p-value*	*Results*
H1	A -> BI	0.211	0.212	0.081	2. 591	0.211	0.054	0. 010	Su pport ed
H2	EU-> A	0.357	0.356	0.086	4. 134	0.357	0.168	0. 000	Supported
H3	EU-> BI	0.252	0.249	0.082	3. 065	0.252	0.087	0. 002	Supported
H4	PB -> A	0.424	0.424	0.087	4. 863	0.424	0.185	0. 000	Supported
H5	PB-> BI	0.309	0.310	0.073	4. 258	0.309	0.102	0. 000	Supported
H6	V -> A	0.110	0.112	0.061	1. 802	0.110	0.021	0. 072	Not Supported
H7	V -> BI	0.210	0.212	0.059	3. 532	0.210	0.092	0. 000	Supported

Note: Significant values at 5% level of significance are in bold italics and ≥ 0.95 for excellent fit. TLI and NNFI values closer to 1 indicate a very good fit, with a value of 1 being perfect. The Comparative Fit Index should be ≥ 0.95 for an excellent fit, with a value closer to 1 indicating a good fit and 1 indicating a perfect fit. The RMSEA value should be ≤ 0.05 for excellent fit, > 0.1 for poor fit, 0.05 to 0.08 for acceptable fit and 0.08 to 0.01 for poor fit. Table 7's value indicates the fitness of the model.

Further, the CFA is used to evaluate the constructs' validity and reliability. Each item's outer loading, indicated in Table 8, validates the reliability of the indicators (>0.5). Furthermore, the data's reliability is confirmed by using Cronbach's alpha (CRA), where a value greater than 0.7 indicates good reliability (Hair *et al.*, 2019). Composite reliability (CR), is used to further analyze the internal consistency and reliability. For each latent construct, the values range from 0.886 to 0.922 within the minimum threshold of 0.70 (Legate *et al.*, 2023). Convergent validity is assessed using the average variance extracted (AVE) and all of the study's constructs exceeded the accepted threshold of 0.5 (Legate *et al.*, 2023).

The discriminant validity between all constructs is shown in Table 9, with the Fornell- Larcker criterion below the recommended threshold of 0.90 (Hair *et al.*, 2019).

Hypothesis Testing

The bootstrap approach was applied to test the hypothesis and the results of the hypothesis testing (Table 10 and Figure 2) testing indicate the relationship between various factors and their influence on attitude (A) and behavioral intention (BI). Hypothesis H1 suggests that attitude has a positive influence on behavioral intention, with a moderate path coefficient of 0.211 and a significant *p-value* of 0.010 supporting it. Hypothesis H2 showed that ease of use (EU) strongly influences attitude (path coefficient = 0.357, *p-value* = 0.000), confirming its support. Similarly, H3 showed that ease of use also directly affects behavioral intention (path coefficient = 0.252, *p-value* = 0.002), so it is also supported. In H4, perceived benefit (PB) has the strongest influence on attitude (path coefficient = 0.424, *p-value* = 0.000), providing strong support for the hypothesis. In addition, H5 showed that perceived benefit positively influences behavioral intention (path coefficient = 0.309, *p-value* = 0.000), supporting it. However, H6, which examined the effect of vulnerability (V) on attitude, is not supported as the path coefficient is 0.110 and the *p-value* is 0.072, indicating a weak and insignificant relationship. Finally, H7 was supported because it showed a positive relationship between vulnerability and behavioral intention (path coefficient = 0.210, *p-value* = 0.000). All hypotheses are supported with the exception of H6, where perceived benefit has the greatest impact on attitude, while ease of use and vulnerability have the biggest effects on behavioral intention.

Table 11: The predictive power of the estimated model

Variables	R^2	R^2 *adjusted*
Attitude	0.619	0.613
Behavioural Intention	0.689	0.683

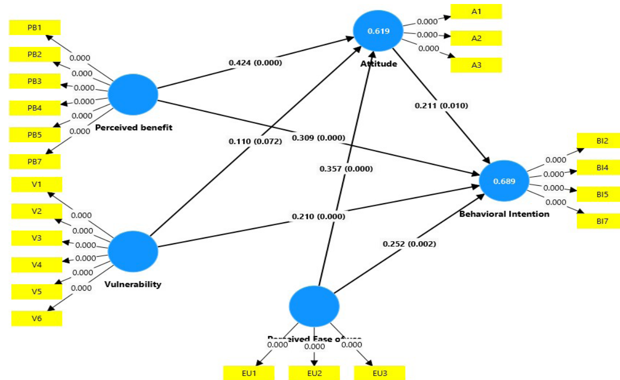


Figure 2: Structural model estimation (Path coefficient and *p-value*)

Table 12: Goodness of fitness test

Construct	*AVE*	R^2	*GOF*
Attitude	0.673	0.619	0.645436
behavioral	0.594	0.689	
Intention average score	0.6335	0.654	0.643668

Note: GoF = (AVE R2) 1/2 0.643668 investment landscape.

Predictive Power Test

According to (Chin, 1998), the R^2 values in the literature indicated that .67 represents substantial variability, .33 as moderate variability and .19 as weak variability. Table 11 findings demonstrate the model's explanatory power of the model for behavioral intention, with 68.9% of changes in intention regarding cryptocurrencies can be attributed to the significant variables in the model. Furthermore, the model also explains 61.9% of the changes in attitudes, which is considered as moderate level of explanatory power.

Model Fit Test

According to Haron and Aziz (2019), the estimated model's fitness is evaluated using the Goodness of Fit (GoF) index. A higher value on this index, which goes from 0 to 1, denotes a better or more reliable model. GoF values of 0.10 indicate a small. 0.25 and 0.36 are considered as medium and large, respectively. This .634438 GoF (Table 12) value indicates a strong fit in the direction of the attitudes and behaviors of retail equity investors.

Discussion

This investigation focussed on studying the attitude and behavior of retail investors of the Indian equity market towards cryptocurrencies. For this, a survey method was used for collecting the data from 200 equity investors. The findings of this study revealed that younger investors, specifically those in the age group of 15 to 35, exhibited a stronger enthusiasm towards the investment platforms, whether it is the equity market or the cryptocurrency market. From the demographic profile, it is shown. However, a large number of investors showed significant interest and awareness about cryptocurrencies, though a small proportion of them had hands-on experience with crypto investments. This shows a potential gap between awareness and actual investment activity among investors. Previous research emphasized various factors that influence investment intention. For instance, factors such as attitude (Nadeem *et al*., 2021; Venkatesh *et al*., 2012), social influence (Arias-Oliva *et al*., 2021), and self-efficacy (Chengyue *et al*., 2021; Lee, 2021) were identified as key motivators for people's decisions to invest in cryptocurrencies. However, this particular study goes a step further to highlight those perceived benefits, such as high returns and long-term growth potential, play a more significant role in shaping investors' attitudes towards cryptocurrency. Further, it finds risks such as policy changes and lack of regulation can significantly impact investors' decisions towards cryptocurrency. These risks or concerns highlight the importance of establishing registered cryptocurrency platforms that are viewed as safe, transparent, and compliant with regulations. Such platforms can address these risks effectively to help build trust among investors. During the study, it was found that investors are interested in cryptocurrencies and believe that the government will regulate them in the future. Furthermore, the study suggests that financial services providers need to understand behavioral factors such as investor attitudes, perceived risks and benefits to develop investment products that specifically meet the demand for secure and reliable crypto investment opportunities. This approach is essential for fostering long-term adoption and sustained growth in the cryptocurrency market.

Findings

To achieve the objective of this study, seven hypotheses were framed, out of which six were confirmed. As earlier discussed, this study highlights that all hypotheses are supported with the exception of H6. Perceived benefit (H4) has the strongest influence on attitude; similarly, vulnerability (H7) also relates to the attitude in a significant and positive manner. However, the influence of vulnerability (H6) on attitude was not validated since the *p-value* exceeded 0. 05, suggesting that the correlation was weak and insignificant.

Furthermore, the findings show that ease of use (H2) and attitude (A1) have a significant positive impact on behavioral intention as its *p-value* is below 0.05 i.e., 0.000. Also perceived benefit (H5) and ease of use (H3) have the significant positive relationship on behavioral intention. Overall, the tested model provided a clearer understanding of Indian equity investors' attitudes and behavior toward investment in cryptocurrency.

Conclusion

For the expansion or development of financial markets, investor preferences are crucial as they have the power to shape the market dynamics. The goal of this study is to investigate the attitudes, understanding and behavioral intentions of Indian retail investors in the stock market towards cryptocurrencies using Smart-PLS and SPSS. Using data from 200 retail investors in stock market, the study systematically examined the following results. The study results indicate a gap between awareness and participation, as a significant number (87.5%) of respondents are aware of cryptocurrencies, but the level of investment is surprisingly low, i.e., 46% of the respondents. The young generation showed more curiosity about cryptocurrency investment, and they are more enthusiastic and optimistic about cryptocurrency. The results showed the influence of perceived ease of use on the attitude and behavior of retail investors. When they find cryptocurrency platforms userfriendly, their investment intentions and attitudes improve (Namahoot & Rattanawiboonsom, 2022; Robkob & Pankham, 2023). They are primarily driven by the potential profits they see in cryptocurrencies, such as higher returns and long-term growth compared to traditional investments. However, vulnerability influences investors' decisions to engage in cryptocurrency transactions. Although investors are aware and concerned about the risk factors associated with cryptocurrencies, such as potential fraud and regulatory difficulties, these issues do not always change their overall perception of them. Finally, attitude and behavioral intention are positively correlated, with multiple factors influencing cryptocurrency adoption. Investors are more likely to participate or interact with cryptocurrencies if they have a positive attitude towards them (Al-Omoush *et al*., 2024).

Limitations and Future Research

As for the constraints of the study, the model is evaluated only in the context of the Indian market and researchers can extend it to a cross-cultural dimension. Another domain with other variables can be added to the research model, such as herding, risk aversion, financial literacy, etc. A large sample provides a more reliable and precise perception. Therefore, a large data set can be used for further studies. Additionally, future researchers can compare the attitudes and perceptions of cryptocurrency investors and stock market investors. Therefore, future research is needed to survey the generalizability of our findings in different contexts.

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Note https://www.businessstandard.com/markets/cryptocurrency https://economictimes.indiatimes.com/markets/cryptocurrency https://timesofindia.indiatimes.com/blogs/v oices/the-evolution-of-cryptocurrencies-inindia-and-what-the-future-looks-like/ https://coinmarketcap.com/

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