Using the Unified Theory of Acceptance and Use of Technology (UTAUT) Model to Study Investors' Buying Behaviour Towards Mutual Funds

Pushpa Raj K.1*, Dr. Shyamaladevi Balakrishnan

ABSTRACT

Manuscript type: Research paper

Research aims: In recent years, we have witnessed tremendous growth in mutual funds in India. There are many reasons behind this growth trajectory, including diversification, compounding, and a lesser involvement of investors in tracking the performances of individual stocks. Technology has allowed investors to choose their funds based on their risk appetite and tenure when they need their investments to mature. The current advancement in digital technology created a more accessible platform for investors to choose different investment vehicles quickly. Mutual funds are among the most well-liked investment choices, for small-scale investors, as they offer steady income over a more extended period with lesser risk. Digitalisation has led more investors to move towards mutual funds as it involves less paperwork to start investing. Also, digital payments have eased investors' lives by allowing them to make payments safely and securely without needing to reach Asset Management Companies (AMCs). In this study, we have attempted to study the impact of different variables that affect mutual fund subscriptions.

* Pushpa Raj K. is a research scholar at the College of Management, SRM Institute of Science and Technology, Kattankulathur-603203, Tamil Nadu, India. Email: pk1077@srmist.edu.in. Correspondence: Tel.: +919940298194

Dr Shyamaladevi Balakrishnan is an Assistant Professor at the College of Management, SRM Institute of Science and Technology, Faculty of Management, Kattankulathur-603203, Tamil Nadu, India. Email: shyamalb@srmist.edu.in

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Design/Methodology/Approach: To demonstrate the causal connection between the various variables, the Structural Equation Modelling (SEM) technique has been employed. We employed a variance-based technique using PLS in our study. With the aid of SmartPLS 3.0, the study model was verified. We follow the normal two-step process, with the first step being the assessment of the measurement model and the second stage is to evaluate models for measurements and structures.
Research findings: The two new additional variables introduced in this study were strongly significant in influencing investors' intention toward Mutual funds. When making decisions about their buying behaviour in the mutual fund industry, retail investors consider data security and additional charges to be key factors. The researcher performed reliability and validity tests, as well as assessed the structural model. The coefficients of determination R2 and Q2 supported the study model and provided evidence of a significant statistical relationship between the independent and dependent variables.
Theoretical contribution/Originality: The present study is important as we see more mutual fund folios are getting piled up every year. Also, with the advent of technology, more account holders are getting into digital space. Understanding the awareness and benefits of using digital platforms among retail investors' decision-making is essential to bringing in more retail participation in the mutual fund industry.
Practitioner/Policy implications: These findings can help investors to make investing decisions and are also helpful for regulators or fund managers to attract more investors.
Research limitation/Implications: The study can be extended to different regions in India or outside of India to study different perceptions of retail mutual fund investors.

Keywords: Mutual Fund Subscriptions, Digital Transactions, Risk-Return Ratio, Fund Performance, Brand Image
JEL Classification: G41

1. Introduction

Technology is growing at a faster pace and its impact has been seen in almost every sector. Technology has been creating a significant impact in the financial sector and mutual funds are no exception. Fintech in the area of mutual fund Know Your Customer (KYC), marketing, distribution, and payments are increasing over the recent years. The mutual fund business has experienced tremendous growth in the use of digital technology, and this growth is accelerating. Several folios under mutual funds and the total net worth of mutual funds are seeing a multi-fold increase in recent years. The development of robo-advisors is founded on the use of predefined programs which can check for the patterns and suggest trading or investment options to stock analysts based on historical performances. We were interested in learning how the Unified Acceptance and Use of Technology (UTAUT) model affected investors' desire to participate in mutual funds, given the rise in mutual fund participants.

Technology has made the process much simpler and easier. Now investments in mutual funds are entirely paperless and much more efficient than previous processes. Fund houses are utilising these technologies to reach a wide variety of investors which they considered as difficult during earlier periods. With the introduction of e-commerce platforms, asset management companies (AMCs) find it easier to market mutual funds to larger audiences. Cloud computing, blockchain, robo-advisors, big data analytics, artificial intelligence, and fintech are redefining the way AMCs are operating.

Mutual funds are seen as an attractive choice for retail investors because of their diverse nature. Furthermore, fund managers who handle the security allocations for mutual funds at a lower cost run them professionally. But retail investors are unique, and they are from a diverse group (Sanesh and Greeshma, 2016). This leaves us to understand the buying behaviour of retail investors to make sure the participation increases in the future.

Venkatesh et. al. developed the UTAUT model in 2003. This model is used to identify the key elements using the user's feedback, assessing the adoption of the newest technology behaviour and usage intentions. We replicated this model to understand the technological impact on the investors buying behaviour toward mutual funds. Venkatesh et. al. proposed four main constructs to identify the level of acceptance for the behaviour and technological intentions, including those related to achievement standards, effort goals, impact on society, and enabling conditions. In this present study, we used the basic architecture explained by Venkatesh and expanded them by including data security and additional charges as two new variables to study the investors' buying behaviour towards mutual funds.

Data security is one of the key features that investors are interested to know before they start with their online transactions either for making a payment or to share their personal information. Mutual funds started adopting these technologies long back and they are directly under the regulations of the Securities and Exchange Board of India (SEBI) which tracks and issues guidelines periodically to make sure all the AMCs are adhering to their guidelines. To avail of these online technologies, mutual fund houses are charging nominal fees to make sure they were able to provide these services without any interruptions and, they didn't take any cut in their profit margins.

Thus, it becomes necessary to study these variables to make sure investors' intentions toward mutual funds buying behaviour is positively oriented. If these variables tend to show any negative impact, then it's the ideal time for fund houses to work towards these areas to make sure investors' data is secured throughout the year. And also, the charges are restructured to make investors feel confident about adopting these technologies with lesser fees.

The main reason for choosing this model is because of its inherent power over eight existing models, including TRA (Theory of Reasoned Action), TAM (Technology Acceptance Model), MM (Motivational Model), TPB (Theory of Planned Behaviour), C-TPB-TAM (Planned Behaviour / Technology Acceptance Model), MPCU (Model of PC Utilisation), IDT (Innovation Diffusion Theory) and SCT (Social Cognitive Theory). The predicted performance of the UTAUT model with all combinations of variables is around 70% (Gunda, 2014). This allows the researchers to build some quality research models for measuring technology adoption.

2. Literature Review

Financial services has been considered one of the sectors which have grown significantly in light of technological development. Individuals can perform either simple fund transfers or can devise a complex derivative strategy with the help of their mobile and internet from anywhere around the globe. The popularity of trading online has increased only because of the availability of historical information and the easier with which a trade can be executed for a low cost.

The adoption of mutual funds in Malaysia was the subject of a research by Abdullah et. al. (2008), examining both awareness and fintech usage using regression analysis. Their study concluded that there is no satisfactory connection between age and gender in terms of performance expectations, social influence, effort expectations, and facilitative conditions. Alexandra Andhov (2018) concluded in his research study that fintech at its nascent stage can adapt based on the knowledge of computer usage, its storage capacities, and intelligent algorithms to support the findings.

Blockchain could benefit its mutual fund stakeholders, according to Prasada Rao et al.'s (2018) study paper with transparency, accountability, tamper-resistance, decentralisation, and privacy. Transparency is required to increase the confidence level of investors and in turn to increase efficiency through digitising the paperwork. Another study conducted by Vijaya Kittu Manda in 2018 concluded that blockchain could be used for net asset value (NAV) calculations and also to process real-time redemption of mutual fund units.

Daniel O'Keefe and colleagues polled about 1500 bank clients (2016), a member of the KPMG group, to better understand their familiarity with and interest in digital asset management. Their findings are surprising with 8-15 % of respondents who are already aware of robo-advisors and started building their portfolio with robo-advisory services.

Though we have newer technologies introduced regularly, the success of these technologies remains in the implementation of these in the financial services industry. Anna Omarini (2017) highlighted this in their research study, and they concluded with a strong statement that stated that the adoption of cutting-edge technologies in the finance industry is essential for disruption to occur.

There are some limitations due to the increased usage of technologies. Teo et. al. (2015) studied the key new fintech businesses' success is impacted by both internal and external factors in China. They found that Connectivity remains a major factor in today's conditions. With the advent of technology, the connectivity medium for fintech companies are mobile devices, the Internet, and social media. They concluded with a note that connectivity is required to become more sustainable in the business. On the other hand, regulations become a key challenge for these new fintech players. As correctly noted in a 2017 report by Santiago Carbo-Valverde titled "The impact of Digitalisation on Banking and Financial Stability," the expansion of financial technology services raises the possibility of laws governing these businesses.

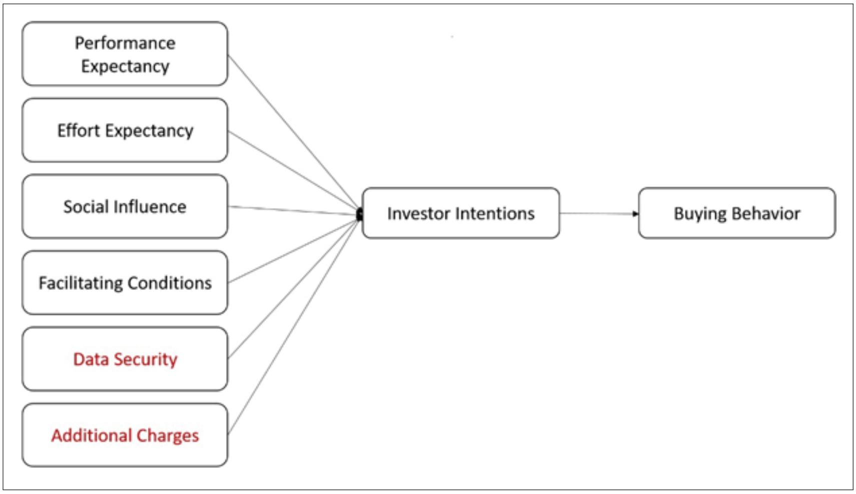
3. Research Gap and Objective

We have several studies wherein researchers have analysed the performance of mutual funds under different categories. Few studies identify the fund manager's skills in timing the market and their stock selections. Numerous studies compare the fund houses and suggest a few funds that are the best performers during the past years. However, the technological impact on the mutual funds sector hasn't been explored yet, and this study aims to do so with the UTAUT model's application, which is becoming more significant in the industry to predict the users' intentions.

We wanted to utilise the UTAUT model and introduce two new variables to study the investor's intentions as well their buying behaviour in mutual funds. We adopted this theoretical framework for the purpose of our investigation.

To investigate a comparison of the effects of performance standards, effort expectations, and social influence, facilitating conditions, data security, and additional fees on investors' intention to purchase mutual funds. Figure 1 shows the Proposed Research Model.

Figure 1: Proposed Research Model



Source: Author's proposal

3.1. *Sampling Method and Data Collection*

The researchers used convenience sampling for this research study. The data collection process which includes populations that are close at hand and can be easily accessible for researchers is called Convenience sampling (Rahi, 2017). It was also explained that researchers can swiftly and affordably obtain the results using convenience sampling (Hair, 2003). Around six hundred mutual fund investors have been approached to get their observations on mutual fund buying behaviour. Researchers ensured the voluntary participation of the respondents and the survey period spreads from February 2022 to March 2022. Respondents were given give two months to submit the survey results. We received around 365 valid responses after performing data cleansing to remove the outliers.

3.2. *Tools Used*

Once all the information from interviewees has been gathered, data analysis can be done, or, as Sugiyono suggests, other secondary sources of data (2017). Model analysis of the primary data has been performed with the use of SmartPLS version 3.3.9 and using structural equation theory (SEM). To evaluate models and hypotheses, SmartPLS has been used.

3.3. *Limitations of this Study*

Social influence, facilitating circumstances, performance expectancy, effort expectancy, and only six constructs included in this research, Data Security, and Additional Charges. This study is confined only to Tamil Nadu state and future studies can include different states to study the investor behaviour in those states and come up with additional suggestions that would benefit Fund houses to concentrate upon in bringing more retail investors participation.

3.4. *Research Methodology*

The questionnaire has been prepared based on the support from prior literature studies. The researcher has categorized the questionnaire into two sections. The participants' demographic data, which includes age, gender, income level, and education level, is covered in the first portion of the questionnaire. In order to represent each variable that we predetermined from prior literature the second portion of the questionnaire asks participants about their behavioural characteristics. Performance expectations, social impact, effort expectations, and facilitating conditions are among the variables and two novel additional variables, data security and additional charges, were taken from Venkatesh et. al. (2012). Seven-point Likert scales, ranging from 1 to 7, have been used to assess each variable. In this section, we'll examine how investors' purchasing habits with regard to mutual funds have an effect on technology.

Below are the null hypotheses for our study:

H1: Performance Expectancy influences investors' intentions in a favourable way.
H2: Effort Expectancy has a positive impact on investors' intention.
H3: Social Influence has a positive impact on investors' intention.
H4: Facilitating Conditions have a positive impact on investors' intention.
H5: Data Security has a positive impact on investors' intention.
H6: Additional Charges have an effect on investors' intentions in a positive way.

H7: Investors' Intention has a positive influence on mutual fund buying behaviour.

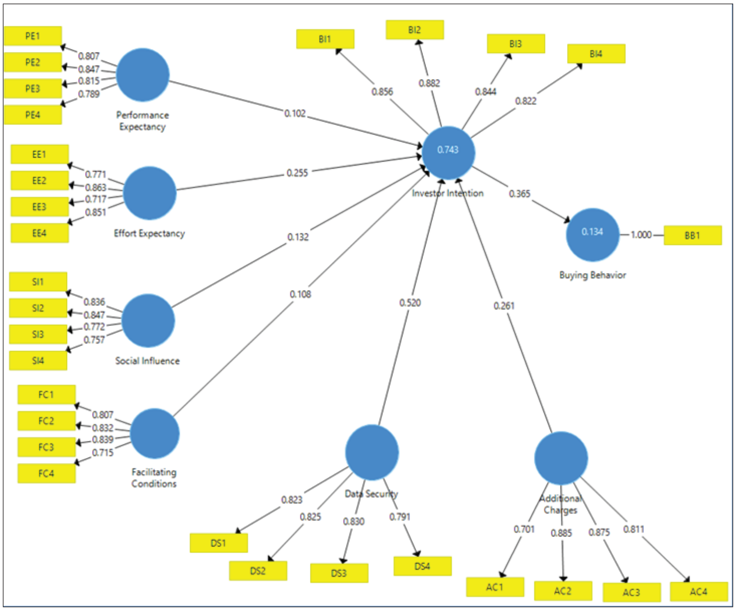
3.5. *Data Interpretations*

In order to demonstrate the causal connection between the various variables, the Structural Equation Modelling (SEM) technique has been employed. We used two types of techniques: SEM Variance based and Covariance based. We employed a variance-based technique using partial least squares (PLS) in our study. With the aid of SmartPLS 3.0, the study model had been verified. (Ringle et al, 2015). We followed the normal two-step process, with the first step being the assessment of the measurement model and the second stage is to evaluate models for measurements and structures.

3.6. *Measurement Model*

We can assess the relationships between various indicators and constructs, as well as relationships within constructs, with the aid of model estimation. When measuring models, we checked the constructs' validity and dependability. The SEM model is shown below in Figure 2.

Figure 2: SEM Model



Source: Author's research work

3.7. *Composite Reliability / Cronbach's Alpha / Average Variance Extracted (AVE)*

When estimating dependability, the internal consistency is assessed using Cronbach's alpha based on the intercorrelations of the factors. In order to verify the reliability based on the factors' outer loadings, we also verified the Composite Reliability as a different measure. Higher reliability is generally regarded as having a composite reliability number between 0.7 and 0.9. Table 1 shows the AVE for Composite Reliability.

Table 1: AVE for Composite Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Additional Charges	0.835	0.837	0.892	0.675
Data Security	0.834	0.838	0.889	0.668
Effort Expectancy	0.848	0.723	0.878	0.645
Facilitating Conditions	0.816	0.842	0.876	0.64
Performance Expectancy	0.831	0.834	0.887	0.664
Social Influence	0.818	0.83	0.879	0.646
Investor Intention	0.873	0.88	0.913	0.724
Buying Behaviour	1	1	1	1

Source: Author's research work

3.8. *Convergent Validity*

A measure that favorably correlates with other measures of the same construct is known as convergent validity. Higher outer loading of value greater than 0.7 marks that the associated indicators have more in common. The commonality of the constructs can be assessed by utilising the Summary of Average Variance (AVE). If the AVE number is greater than 0.5, then each construct accounts for more than 50% of the variance in the indicators. Our data indicate that AVE values greater than 0.5 are considered acceptable for convergent validity based on the aforementioned Table 2.

Table 2: Convergent Validity

	Additional Charges	Data Security	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence	Investor Intention	Buying Behaviour
AC1	0.701							
AC2	0.885							
AC3	0.875							
AC4	0.811							
DS1		0.823						
DS2		0.825						
DS3		0.83						
DS4		0.791						
EE1			0.771					
EE2			0.863					
EE3			0.717					
EE4			0.851					
FC1				0.807				
FC2				0.832				
FC3				0.839				
FC4				0.715				
PE1					0.807			
PE2					0.847			
PE3					0.815			
PE4					0.789			
SI1						0.836		
SI2						0.847		
SI3						0.772		
SI4						0.757		
BI1							0.856	
BI2							0.882	
BI3							0.844	
BI4							0.822	
BB1								1

Source: Author’s research work

3.9. Discriminant Validity

AVE scores are compared to the correlations of latent variables based on their square roots variables using the Fornell-Larcker criterion for discriminant validity and ensured that AVE values are highest among the other constructs. This confirms that constructs share the highest variance with their associated indicators than any other constructs. Table 3 shows the Discriminant Validity.

Table 3: Discriminant Validity

	Additional Charges	Buying Behaviour	Data Security	Effort Expectancy	Facilitating Conditions	Investor Intention	Performance Expectancy	Social Influence
Additional Charges	0.821							
Buying Behaviour	0.401	1						
Data Security	0.683	0.354	0.817					
Effort Expectancy	0.195	0.059	0.161	0.803				
Facilitating Conditions	0.381	0.108	0.437	0.539	0.8			
Investor Intention	0.707	0.365	0.811	0.078	0.448	0.851		
Performance Expectancy	0.369	0.119	0.364	0.62	0.573	0.381	0.815	
Social Influence	0.463	0.174	0.524	0.577	0.697	0.522	0.669	0.804

Source: Author's research work

3.10. Analysis of Structural Model

Assessment of Structure Model includes the model's ability to forecast outcomes and the relationship between the constructs. To avoid any kind of biases we need to assess the collinearity between the predictor constructs.

3.11. Collinearity

Collinearity can be calculated based on Tolerance. Tolerance indicates a variable's variance that cannot be described by another indicator within the same area. The term "variance inflation factor" refers to tolerance's opposite. (VIF). There may be a collinearity issue when the VIF number exceeds 3.3 (Diamantopoulos and Siguaw, 2006). As per our below table for Outer and Inner Collinearity, all the values are below 5 or 3.3 and our data is free from any collinearity issues (Hair et al, 2014).

3.12. *Outer Collinearity: (VIF)*

Table 4 Shows the Outer Collinearity (VIF).

Table 4: Outer Collinearity (VIF)

	VIF
AC1	1.337
AC2	3.191
AC3	3.105
AC4	1.758
BB1	1
BI1	2.132
BI2	2.389
BI3	2.114
BI4	1.973
DS1	1.783
DS2	1.789
DS3	1.857
DS4	1.738
EE1	1.738
EE2	2.084
EE3	2.289
EE4	1.719
FC1	1.726
FC2	1.727
FC3	1.741
FC4	1.558
PE1	1.752
PE2	2.051
PE3	1.709
PE4	1.691
SI1	1.949
SI2	1.871
SI3	1.507
SI4	1.626

Source: Author's research work

3.13. Inner Collinearity (VIF)

Table 5 Shows the Inner Collinearity (VIF).

Table 5: Inner Collinearity (VIF)

	Investor Intention	**Buying Behaviour**
Additional Charges	1.946	
Data Security	2.193	
Effort Expectancy	1.941	
Facilitating Conditions	2.144	
Performance Expectancy	2.198	
Social Influence	2.885	
Investor Intention		1
Buying Behaviour		

Source: Author's research work

3.14. Hypothesis Testing

Path Coefficients were used to analyses the proposed connection between the constructs. Usually, path coefficients range from -1 to +1 in worth. Values closed to +1 are considered to be exhibiting a positive relationship and in turn, confirm mathematical significance, which they possess. The chart below indicates this, our data suggest that all our hypotheses are statistically significant as the p values are lesser than 0.05. We performed bootstrapping around 5000 times and calculated T Statistics for the 0.05 significance threshold for a one-tailed test. T-Table (one-tailed) value for 0.05 significance level is around 1.65. We compared this against the results based on our data to analyse the strengths of exogenous variables on the endogenous variables without any moderating indicators. Table 6 shows the T-Statistics results.

Table 6: T-Statistics results

	Original Sample (O)	**T Statistics**	**P Values**	**Results**
Performance Expectancy -> Investor Intention (**H1**)	0.102	1.887	**0.030**	Supported
Effort Expectancy -> Investor Intention (**H2**)	0.255	3.019	**0.001**	Supported
Social Influence -> Investor Intention (**H3**)	0.132	2.547	**0.006**	Supported

	Original Sample (O)	T Statistics	P Values	Results
Facilitating Conditions -> Investor Intention (**H4**)	0.108	2.449	**0.007**	Supported
Data Security -> Investor Intention (**H5**)	0.520	11.239	**0.000**	Supported
Additional Charges -> Investor Intention (**H6**)	0.261	5.660	**0.000**	Supported
Investor Intention -> Buying Behaviour (**H7**)	0.365	7.566	**0.000**	Supported
Note: Significance level where $p < 0.05$				
Source: Researcher processed data				

Source: Author's research work

Results of the structural model reveal that all our hypothesis exhibits a statistically positive relationship with their corresponding endogenous variables.

3.15. Determiner Coefficient (R^2)

The predictive accuracy of our algorithm is assessed using the Coefficient of Motivation (R^2). R^2 has a number between 0 and 1; values closer to 1 denote prediction accuracy that is higher. R2 values of 0.75, 0.50, and 0.25 Researchers can classify these results as significant, mediocre, and weak, accordingly, for latent endogenous variables (Hair et al, 2011 and Henseler et al, 2009). The statistics are acceptable, as indicated by our data's R^2 value of 0.743 (Cohen 1988). Table 7 shows the Coefficient of Determinations (R^2).

Table 7: Coefficient of Determinations R^2

	R Square	R Square Adjusted
Buying Behaviour	0.134	0.131
Investor Intention	0.743	0.739

Source: Author's research work

3.16. Effect Size (f2)

The term "Effect Size" pertains to the change in R^2 value that happens when a certain exogenous construct is removed from the model and the effect that removal has on the endogenous construct (f^2). Table 8 shows the Effect Size (f^2).

Table 8: Effect Size (f^2)

	Investor Intention	Buying Behaviour	Significance
Additional Charges	0.137		Small
Data Security	0.481		**Large**
Effort Expectancy	0.13		Small
Facilitating Conditions	0.021		Small
Performance Expectancy	0.019		Small
Social Influence	0.023		Small
Investor Intention		0.154	**Medium**
Buying Behaviour			

Note: f^2: 0.02 - small; 0.15 - medium; 0.35 – large
Source: Author's research work

To calculate the value for Q^2, we used the formula below by Hair et. al., 2012:

$$Q^2 = 1 - (1 - R1^2)\ (1 - R2^2) \ldots (1 - Rp^2)$$
$$Q^2 = 1 - (1 - 0.743) \times (1 - 0.134)$$
$$Q^2 = 1 - (0.257 \times 0.866)$$
$$Q^2 = 1 - 0.22$$
$$Q^2 = 0.78$$

The data used in this study is more diversified and the amount of diversity as explained by this model is around 78%. Hence, we can consider that this structural model has good fitness for use.

4. Conclusion

Based on the data analysis and interpretations we found that this study's research model has a greater degree of accuracy in predicting investors' purchasing behaviour. Variables from the underlying model; i.e. expectations for performance, effort, social influence, and enabling circumstances are supported well with the research model without any contradictions. Also, the two new additional variables introduced in this study were strongly significant in influencing investors' intention toward Mutual funds. When making decisions about their buying behaviour in the mutual fund industry, retail investors consider data security and additional charges to be key factors. The researcher performed reliability and validity tests, as well as assessed the structural model. The coefficients of determination R^2 and Q^2 supported the study model and provided evidence of a significant statistical relationship between the independent and dependent variables.

5. Scope for Future Work

Future researchers can extend this study by including additional variables like risk return, technology awareness, internet awareness, etc. More number of indicators like age, gender, income, etc. can be added to ascertain the impact of these additional indicators on the intentions of investors over mutual funds buying behaviour. Moderating variables such as age, gender, and voluntariness are included in the fundamental UTAUT paradigm, but are not included in this study. This study can be enhanced by including these moderators to study the fintech impact on the investor buying behaviour towards mutual funds in the upcoming research studies.

6. Data Availability Statement

All the data is collected from the simulation reports of the software and tools used by the authors.

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Appendix: Survey Instrument

Variables	Items	Questions
Performance Expectancy	PE1	Fintech enables me to accomplish my tasks quickly (Purchase / Redeem) Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	PE2	Fintech allows me to make decisions appropriately and timely Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	PE3	Fintech improves my knowledge about mutual fund investments Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	PE4	Fintech provides me with historical performances of the funds instantly Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
Effort Expectancy	EE1	Fintech makes it easier for me to manage my portfolio Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	EE2	Fintech is much more easier than previous processes Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	EE3	Fintech transactions are simple and easy to navigate Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	EE4	Fintech learning is much easier Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
Social Influence	SI1	Fintech is already adopted by friends who suggests me to use these technologies Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	SI2	My Financial Advisor advised me to adopt these Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	SI3	Asset Management Companies promote these Fintech services widely to adopt Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	SI4	AMFI advices investors to adopt these Fintech services to ease our investment worries Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree

Variables	Items	Questions
Facilitating Conditions	FC1	Mutual fund Distributors provides all the access information's to use the Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	FC2	I have sufficient knowledge to use these Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	FC3	Fintech services are similar to other technology which we use on daily basis Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	FC4	Support services are offered timely to resolve any Fintech errors Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
Data Security	DS1	I feel my Data is secured while using these Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	DS2	I don't have any fear of data compromise on these Fintech platforms Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	DS3	I am not worried while making payments or redemption via these Fintech platforms Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	DS4	SEBI is monitoring these Fintech platforms regularly and I am confident my data is not compromised Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
Additional Charges	AC1	Fees charged by these Fintech services are fairly priced Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	AC2	I don't have to feel like paying hugely for using these Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	AC3	Fintech platforms are charging nominal fares for using their platforms Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	AC4	Our investments are safe and secured for which paying reasonable fees is acceptable Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree

Variables	Items	Questions
Investor Intention	II1	I intend to continue using these Fintech services in the future Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	II2	I have adapted to these Fintech services as my daily routine Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	II3	I started using these Fintech services regularly analysing my portfolio Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
	II4	I intend to try any new Fintech services in the future Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree
Buying Behaviour	BB1	I am ready to buy Mutual funds' investments through these Fintech services Strongly Disagree:_1_2_3_4_5_6_7_:Strongly Agree