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Revealing The Potential of Online Mutual Fund Applications by Examining Continuous Investment Intentions: Multistage Integrating Approach SEM-ANN-NCA

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ABSTRACT

The growing adoption of online mutual fund applications highlights how digital transformation is reshaping investment behavior. This study explores the antecedents of continuous investment intentions by integrating TAM, ECM, and ISSM through a multi-phase ANN-SEM-NCA approach. Data from 850 Indian mutual fund investors were analyzed to assess the impact of perceived usefulness, confirmation, trust, and user interface on behavioral intentions and continued investment. ANN sensitivity analysis identified confirmation as the most critical factor, emphasizing the role of platforms in meeting user expectations. Findings suggest the necessity of interactive and customizable content in user-centered design to enhance engagement and retention. This study advances post-adoption behavior literature and provides actionable insights for FinTech platforms aiming to improve user retention. Future research should expand to international contexts and incorporate extrinsic economic factors to enhance generalizability.

Keywords: Digital investment intention, Fintech adoption, Technology Acceptance Model, Expectation confirmation model, Information system success model, Investment behaviour, Continuous investment intention, Structural equation model-Artificial neural network- Necessary condition analysis (SEM-ANN-NCA)

1. Introduction:

The advent of online mutual fund platforms has transformed investing practices by providing investors with a streamlined and effective method for portfolio management. The rapid development of digital technology and the internet has transformed financial technology (FinTech) (Al Nawayseh, 2020). As digital technologies become more prevalent, investors are transitioning from conventional investing techniques to online platforms that provide enhanced accessibility, transparency, and tailored experiences (Saleem et al., 2021). As stated by (Lim D.J. and Hur Y. and Park K., 2019), online mutual fund apps have become indispensable for investing, providing investors with straightforward, efficient, and accessible platforms for managing and enhancing their assets. In India, the exponential expansion of mutual fund investments needs a critical knowledge of the motivations of online mutual fund investors to continue this trend.
The quantity of mobile app-based investors in India increased by 55% in 2021, highlighting the digital transformation in investment behaviour (Sandeep et al., 2021). Statista (Basuroy, 2024) forecasts that the total value of transactions in India's digital investment industry is projected to reach $148.10 billion by 2024. As of February 2024, mutual funds in India managed an AUM of INR 54.54 trillion, a significant rise from INR 9.16 trillion in 2014, indicating a six-fold growth (Rukhaiyar, 2024).
The current research has explored variables such as perceived usefulness (PU), perceived ease of use (PEOU), system quality, and trust as determinants of investor behaviour, there has been insufficient focus on the factors affecting continuous investment intentions, which are essential for user retention (Silwal & Bajracharya, 2021). The research conducted by (Che Hassan et al., 2023; Malaquias A.F., 2020; Yuan Y. and Yao R. and Liu J., 2016) examined how characteristics such as perceived relatedness, trust, confirmation, and system quality affect investors' investing behaviour and loyalty. Online mutual fund apps integrate financial decision-making with digital user experiences, necessitating a holistic strategy to comprehend user investing behaviour. This

study seeks to amalgamate existing models, including the Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Information Systems Success Model (ISSM), as referenced by (Dewi & Rahadi, 2020; M. Zacky et al., 2024; Nurjanah et al., 2020; Saputri et al., 2024; Slade et al., 2015; Sreelakshmi S.K., 2020; Talwar et al., 2020; Wu et al., 2020; Zhao F., 2021). Furthermore, this is a distinctive effort to combine these models for use in the context of online investing activity.
Frameworks such as TAM and ISSM have analysed pre-adoption behaviours on generic platforms, but their applicability to post-adoption behaviours in financial services is constrained. The use of ECM, recognised for its emphasis on user pleasure and retention, enhances the theoretical framework of the research. This amalgamation of TAM, ISSM, and ECM offers a comprehensive framework that encompasses both pre-adoption and post-adoption stages, while including distinctive factors like as interactivity, relatedness, user interface, fun, and confirmation, which are essential in the context of financial decision-making. The study provides extensive insights into the behavioural dynamics of mutual fund investors by addressing existing gaps, fulfilling a crucial need in the changing digital investing landscape.
Thus, the study aims to focus following investigation;
RQ1: “What are the key factors and underlying connections that influence investor’s intention and continuous investment intentions on digital investing platforms?”
RQ2: “How do their relative importance and necessary, sufficiency levels contribute to shaping investment behavior?"
The findings aim to guide developers and financial organizations in enhancing online mutual fund platforms to improve user retention and loyalty in a highly competitive and complex market.

2. Theorical Framework:

(Delone & McLean, 2003) created the Information Systems Success Model (ISSM) as a cohesive framework for evaluating the efficacy of information systems. ISSM was established to address the intricate challenges associated with measuring and defining IT performance (Talwar et al., 2020; Yuan L. and Su B. and Zhang H., 2020). The ISSM integrates the assessment of online mutual fund displays. As per the AIS source, it is founded on user interface, perceived relatedness, and engagement, which influence long-term benefits and use habits (Aldholay O. et al., 2018) .This pertains to online mutual fund investment. The use of ISSM aids in determining the impact of system, information, and service quality on an investor's intention and propensity to persist in using that platform (Hsu L.-W. and Hsu C.-S., 2014).
The TAM paradigm is well established for comprehending how investors adopt new technologies (Davis, 1989). TAM is essential for analysing the investing behaviour of investors (Ahmed et al., 2014; Lee & Lee, 2019). Distinct TAM factors appropriate for online mutual fund investment (Franque T. and Tam C., 2021).
(Bhattacherjee, 2001a) established the ECM paradigm, which elucidates the factors influencing investor technology/system use decisions post-adoption. The model examines the influence of investors' expectations, efficiency assessments, and satisfaction on their technology utilisation (Gao et al., 2015; C.-Y. Li & Fang, 2019). ECM elucidates the reasons clients persist in using the online mutual fund investment application (Singh, 2020). Ensuring the program meets their expectations and provides a positive overall experience will likely increase investor engagement (Gao et al., 2015; Hsu & Lin, 2015; F. Li et al., 2021). This is particularly significant for evaluating post-adoption behaviour in financial services, where trust and continuous involvement are crucial (Sreelakshmi Sangeetha K., 2020).
The integrated model enables researchers to examine the impact of user interface, perceived relatedness, and engagement on an investor's long-term financial returns. This research used the Technology Acceptance Model (TAM) to examine the ongoing motivations for using an e-finance platform, while considering the advantages of integrating TAM with other models for a comprehensive understanding of the context. Researchers undertook this research to determine the feasibility of cultivating trust and fun. The ECM theory analyses post-usage behaviour, illustrating how online mutual fund investment is sustained by expectations, USE, and CON factors. These theories provide a thorough framework for analysing current objectives in an online mutual fund application.

2.1 Hypothesis development:

The user interface (Dalimunthe & Suryani, 2024) is the viewpoint of the e-commerce interface of investors on the website. Based on (Koo Y. and Park K. and Lim M.K., 2011), the user interface comprises menus, navigation, interaction, and other mobile device controls. According to (Liu Q., 2018) the simplicity and usefulness of the user interface depend critically on Simple transactions and trust-building user interface of the user interface help to simplify transactions (M. Zacky et al., 2024). User interface has been under much study in connection with aim for reinvestment. Strong service quality and a simple interface help to increase investor repeat business and retention. Improving investor satisfaction and reinvestment intentions by means of user interface and service quality increases (Shao et al., 2020). The material has led one to formulate the following theory.

H1: UINT significantly influence INVI to mutual fund investors.

Perceived Relatedness (PRL) refers to the information quality provided by a source (Yan et al., 2021). The kind of information provided by an agent investing in mutual funds could in this way include prevailing market conditions as well as statistical data on a fund's products. The relatability of this information is critical, because it is what customers rely on in order to make intelligent decision about purchasing or selling mutual fund products (Sitar-Tăut, 2021). Prior research has shown that content relevance may affect user satisfaction in information systems. According to research done by (Oghuma et al., 2016) show strong correlation between user satisfaction levels and the service or content quality offered by smart technology. Therefore, the following hypothesis is proposed:

H2: PRL significantly influences INVI to mutual fund investors.

Interactivity (INTR) refers to the investor's perception that the information system can quickly respond to their questions. According to (Al nawayseh, 2020), this is equally important for fixed-income fund investment applications as it is for anything else. Changes in the stock market get up-time for a program to process user requests, and then get across to users the prices they want quickly enough when they buy or sell funds. If a member of their own community can do it from wherever there close by at less than 0.25 Mbps speed, then they will have happy stakeholders, making applications such as these highly liked and also achieving high marks in reviews (Sohaib et al., 2020). Hence the following are postulated:

H3: INTR significantly influence INVI to mutual fund investors.

USE (perceived usefulness) is the degree to which an individual thinks that utilising information technology would improve their performance at work (Venkatesh R, 2017). This leads to user views regarding technology's ability to enhance work performance (Alalwan et al., 2016). Prior researchers have consistently shown that USE strongly influences users' preferences for engaging with information systems (Murad et al., 2020). The study by (Fatmawati & Ali, 2021) that perceived usefulness strongly affects consumer happiness and the intention to persist in utilizing the internet on mobile devices. As a result we assume:

H4: USE significantly influence INVI to mutual fund investors.

Confirmation (CON) investigates the extent to what users feel their initial expectations are realized for an application when actually using it (Brown V. and Goyal S., 2012). In this light, confirmation will determine how well the program satisfies the investor's demands. In addition to confirmation, some previous studies also used the term "disconfirmation" to mean the same thing. Another research finding (Brown V. and Goyal S., 2014) was that user expectations for mutual fund investment applications can be validated by user's experience and the quality of service provided by application. If user experience meets or exceeds initial expectations, confirmation will be user satisfaction, because the advantages one anticipates from information system utilization can actually be realized (Chen H.L. and Hsu Y.C., 2010). If the user's investing wishes are met, they will be satisfied with the mutual fund investment application they employ; if not, vice versa. So we predict that:

H5: CON significantly influence INVI to mutual fund investors.

The level of mutual trust (TST) developed between the investor and the investment goal determines the complex relationship between them (Guiso et al., 2008). This relates to how much investors trust online mutual fund companies in terms of their implemented privacy and security measures (Alalwan, 2020). Because it offers a strong framework for comprehending investors' adoption and use of electronic resources, online behaviour analysis highlights the need of adding a confidence component to acceptance models. Prior studies (Fang I. et. al., 2014)have demonstrated that trust has a favourable impact on the propensity to engage in online transactions. As with interpersonal trust, trust in technology is made up of two parts: trusting beliefs and trusting purpose (Roca et al., 2009). Therefore, it is suggested that,

H6: TST significantly influences INVI to mutual fund investors.

Perceived playfulness (PLF) refers to the pleasant feeling people have when they use an information system or similar service (Koenig-Lewis et al., 2015). A by-product of that attitude might also be described as: comfort with information technology. In applications of mutual funds investment, shareholders feel comfortable and satisfied at surprising profit succeeds. Earlier work (Ahn et al., 2007) suggests that perceived playfulness significantly promotes user satisfied and willingness to continue. The untiring of environmental servant's comfort in a country in which people depend on information technology for their living should then increase their enjoyment of and comfort levels with the system. In this way it is held that:

H7: PLF significantly influence INVI to mutual fund investors.

The theory of(Ajzen, 2002), posits the presence of a direct causal link between investor's intention and conduct. When someone can change one's actions or statements, it shows the attitude of a person (Raut et al., 2018). When somebody is allowed to be prepared for the intention, including trust, confirmation of accuracy and user help compounds, her/his chance of such action practices will rise (Sashikala & Chitramani, 2018). (Cuong & Jian, 2014) argued that psychological features such as relational uncertainty, confidence, following the majority, interactivity as well as others have a significant impact on an individual's investment intention, while (Mishra et al., 2023) showed for at least one such factor (investment interest) there is a positive correlation. The primary aim of the study is to find out how investors consider their intentions towards mutual fund investing and which objectives predominantly influence their ongoing investment intentions. Therefore, we put forward our suggestion for this as follows:

H8: INVI is positively influencing CINI to mutual fund investors.

3. Research methodology:

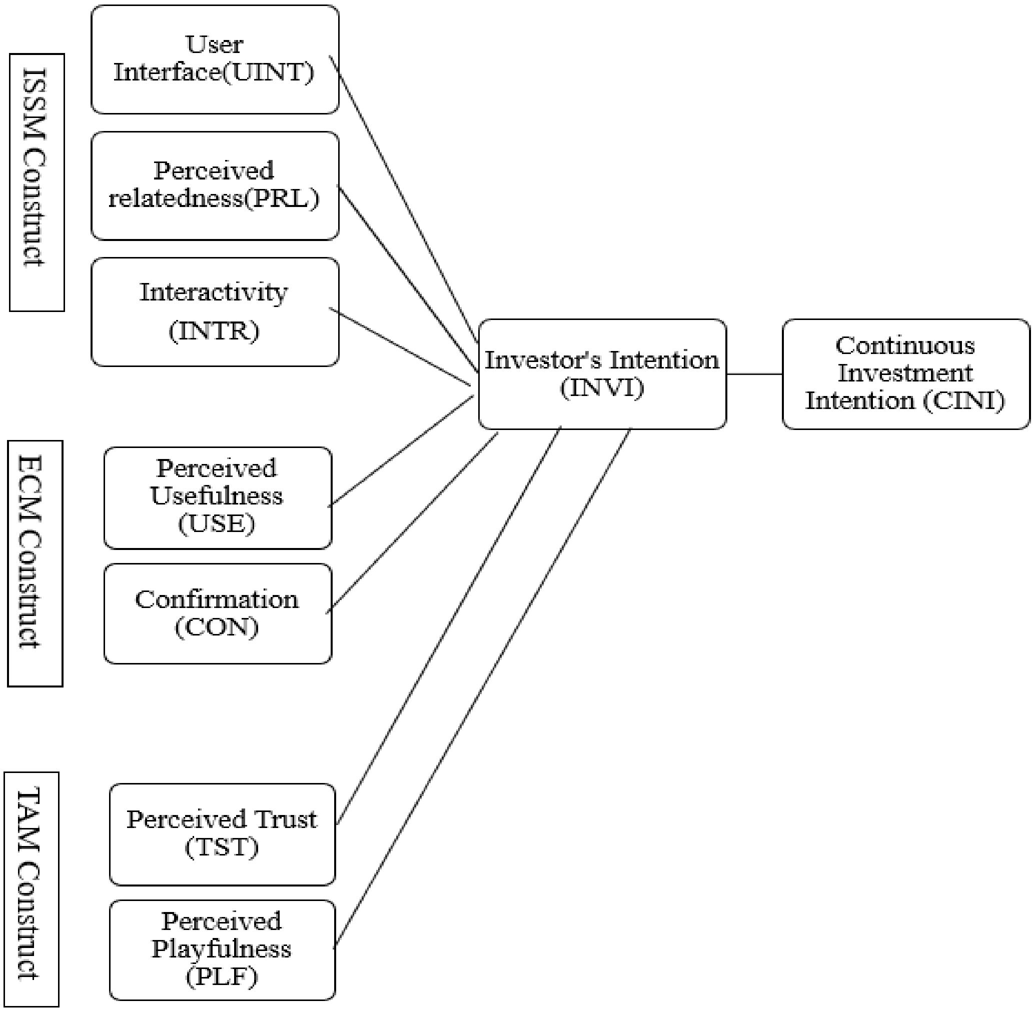

Figure 1: Structural Model

3.1 Demographic characteristics and Measurements:
(Demographic profile attached as Appendix 1).
3.2 Measurement of Variables:
Multiple qualities were evaluated using thorough measurement. Participants answered 38 items were classified in 9-variables. Former research scales were amended so as to measure constructs (Appendix table 2). The Likert Scale ranged from "strongly disagree" to "strongly agree" (1-7). User Interface (UINT) and PRL were each assessed on a four- and three-item scale respectively ((Hwang & Kim, 2007); (Deci & Ryan, 2000)). Interactivity (INTR) was considered in 4 items and Usefulness (USE) in 5 items (Liu & Shrum, 2002). Thus, (Venkatesh & Davis, 2000) Four questions and six questions assessed Confirmation (CON) and Trust (TST) (Bhattacherjee, 2001b; Grabner-Kräuter & Kaluscha, 2003). A four-question scale assessed Perceived Playfulness (PLF) (Moon & Kim, 2001), while Investor Intention (INVI) and Continuous Investment Intention (CINI) were each tested in 3 questions (Bhattacherjee, 2001b). The test has two parts: that is a seven-point Likert scale on the extent to which elements are present and demographic data about investors. Education was divided into five stages, and gender, age, and income were rated on nominal scales from two to four levels.

3.3 Pre and pilot testing:
A systematic questionnaire was created using a validated scale and a conceptual framework based on earlier research. Conceptualpletion questionnaires were based on this previous research Standardised questions were conducted by three experienced financial experts to guarantee clarity and research reliability and validity. These questions were designed in such a way that participants assessed for criteria validity and to ensure understanding and accuracy. A group of specialists morphed the questionnaire's structure, wording, sequence

and supplementary paper to ensure face and content validity. Industry experts performed internal practice trials to understand the ladder structure and integrate panel suggestions before data collection. A pilot study of 58 mutual fund investors from an actual and coherent community in Ahmedabad. Internal consistency and category definitions are validated by pilot testing of the structured questionnaire. IBM SPSS 26 was used for initial testing. Data analysis showed that Cronbach's alpha coefficients were over 0.70 (Chou & Bentler, 1995). This takes in the reliability of the data and internal consistency for each of nine pre-designated constructs being confirmed.

3.4 Target Population and Sampling Design:

The research aimed at helping mutual fund investors better understand the potential consequences of their investment choices. The questionnaire was completed by individuals who are skilled in the use of technology and make their investments online or on paper. As a result, the respondents contained investors who are also users of a mobile application that makes investing easier. Those taking part were experienced investors with a thorough understanding of financial terms and the ability to handle market risks and unpredictability, showing ability, rich experiences and financial literacy. The research was conducted in major cities in Maharashtra and Gujarat, two states known for their investor-friendly policies and strong economic climates, where over 40% of the contributions to our investments comes from. Because it is impossible to compute a sample size, a non-probability judgemental sampling method has been used. When the sample attributes have been predesigned, this method will give results.

3.5 Data Collection Process:

The survey lasted for four months, i.e., from February to May 2024. We gathered data from a number of major cities where the environment is favoured by investors. The survey found an average reaction time of twenty-three minutes. Before the survey began, participants received detailed explanations on both the nature and targets of our undertaking. Their responses were thereby protected in total confidentiality.

With 852 complete replies acquired from a group of investors, we completed rational SEM analysis as required (Myers et al., 2011). The observed sample size according to investigators was ten times the number of responses produced on structured questionnaires, exceeding the benchmark value (Anderson et al., 1988). Additionally, the G Power 3.1.2 application was used to calculate the minimum sample size for a given study. The parameters applied in the computation consist of an impact size of r = 0.50, mean effect size 0.15 and target variation margin 0.05. The survey results show that a sample size of 315 is indeed appropriate; but the actual sample size exceeds recommended levels depending on simulated data. A sample size of 852 is adequate for ANN studies as long as it is at least ten times the number of synapse weights in an existing ANN model. In the second stage of the ANN approach, seven major externally-oriented variables together with a mediator variable were used (852 > 50*8 = 400) to forecast the behaviour of continuous intention to invest.

4. Empirical Results:

4.1 Assessing CMB (Common Method Bias) and Non-Response Bias:

Every cross-sectional study of human behavior is at least partly susceptible to Common Method Bias (CMB) (Jordan & Troth, 2020). The common method bias (CMB) issue can crop up when endogenous and exogenous variable data are collected totally in using accepted scales. We took the study in two directions therefore, in order to verify that there were no CMB-related problems in the dataset: qualitative approaches were used to elicit data as well as direct and more quantitative research methods (Leong, Hew, Ooi, Lee, et al., 2019). None of them questions have a "right" answer of course, and participants were made well aware this before. Also, guaranteed was the confidential protection of personal data.

Statistically analysing it finds that using Harman's single-factor test, a recovery rate was generated below the 50 percent requirement condition. Calculated this way, the analysis is in line with existing theory: our dataset does not show accurate representation for CMB (Podsakoff et al., 2003). To overcome the drawbacks of Harman's single-factor method, CMB was judged using other more nuanced techniques (Harman, 1976). The first assessment of CMB (Kock & Lynn, 2012) used VIF data from the factoring and collinearity test. The test revealed that every construction's VIF value simultaneously dropped below 3.3 threshold in an independent control block and the entire collinearity test. The study computed VIF for each scale item and variable (Kock, 2015). In the data used here, the VIF value for every scale factor and for every variable in the dataset always falls below that 5-point threshold (O'brien, 2007). Based on the procedural components as well statistical evidence analysis described above, the given dataset in this way lacks Common Method Bias (CMB).

4.2 Multivariate Assumption:

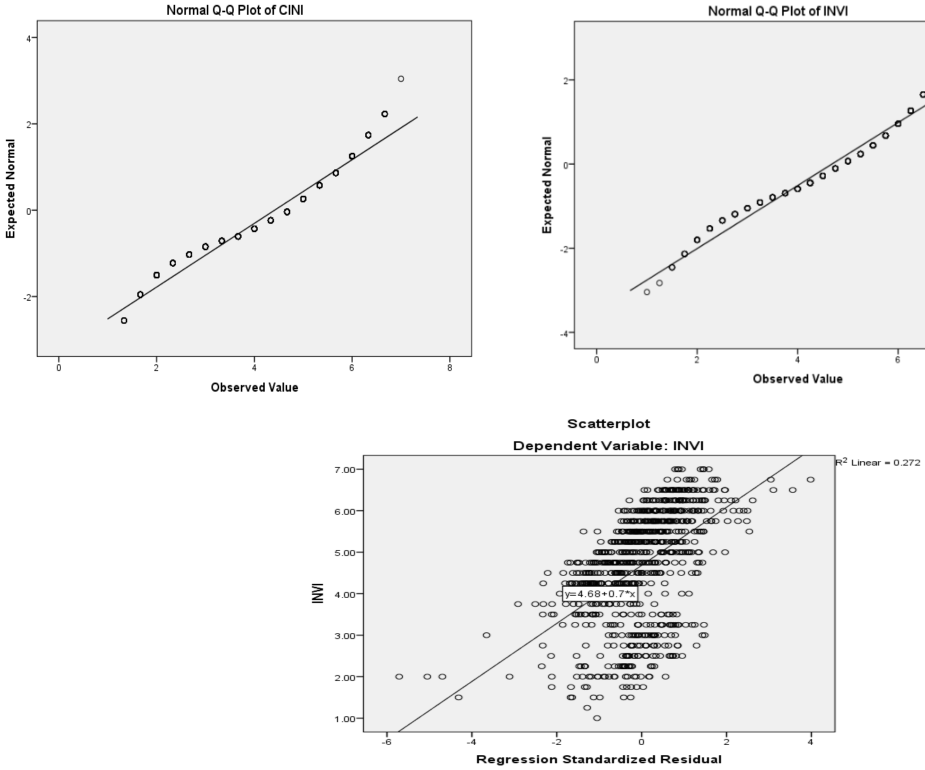

Figure :2

Numerous empirical tests were done in advance in order to understand the properties of the data shall presume to stubbornly deduct, before the final structural model is performed. Normality for data this was conducted before beginning multivariate analysis. The statistical methods for analysis of data during entry into this program are the Shapiro-Wilk test and QQ plots. As we can see from the test results, behavioral intention and an investment commitment are key. But the QQ plots of these two variables most dramatically show that present data does not follow a normal distribution as seen in Figure 2.
To assess linearity of the data, the test deviates from linearity and is conducted with all necessary latent constructs. The finding shows, all significant values < 0.05, signifying linearity in the current dataset Multiple regressions have been conducted in the regression analysis. Normalize values and residuals to assess homoscedasticity and potential outliers. The data shown in Figure 2 has a scattered dot pattern with no discernible linear trend. The findings indicate that the assumption of this study, homoscedasticity, was satisfied.
Furthermore, Levene's test is conducted to see whether the variance of the continuous investment group [Appendix Table: 03]; significant values are 0.759, meaning that these exceed 0.05, indicating equal variance among groups and thus that this assumption of homogeneity in variances (homogeneity assumption) has been met. As evidenced by the aforementioned statistical results, it is apparent that SEM-ANN and NCA methods should be employed for multi-stage testing.

4.3 Assessing Measurement Of The Model:

With regard the reflective model into consideration of both validity and reliability (Hair C.M. and Sarstedt M., 2011). The AVE must above 0.5, and the minimum acceptable values for outer loading and CR should be greater than 0.7 (Hair M. and Ringle C.M. and Mena J.A., 2012). Table 1 presents the Average Variance Extracted (AVE), convergent reliability (CR) and outer loading measured in this study. This table shows that all the variables fall into a narrow band with no single values above or below it. Consequently, there is very little discrepancy between any two points on line for each factor. As shown in Table 1: Outer loading, Composite Reliability, and all values are greater than 0.7. In addition, AVE values are all greater than 0.5.
According to (Henseler et al., 2015), the HTMT ratio is used to evaluate whether discriminant validity can be reached. The acceptable range for the HTMT ratio is less than 0.85. Tables 2 and 3 present the results of the HTMT ratio. The study s findings have demonstrated concurrent and discriminant validity for the reflective scale.

RELIABILITY AND CONVERGENT VALIDITY (TABLE-1)

Construct	Factor Loading (Min-Max.)	Cronbach's Alpha(A)	Dijkstra-Henseler's Rho_A	Joreskog's Rho_C	The Average Variance Extracted (Ave)	VIF Range
CINI1	0.885-0.905	0.874	0.874	0.922	0.798	2.249-2.595
CON1	0.847-0.869	0.883	0.884	0.919	0.741	2.270-2.525
INT1	0.890-0.914	0.891	0.892	0.932	0.821	2.346-2.849
INVI1	0.859-0.872	0.891	0.892	0.925	0.754	2.286-2.454
PLF1	0.761-0.892	0.877	0.883	0.915	0.730	1.371-3.801
PRL1	0.837-0.864	0.807	0.813	0.886	0.721	1.713-1.809
UINT1	0.766-0.907	0.892	0.896	0.926	0.759	2.947-3.304
USE1	0.747-0.905	0.919	0.921	0.940	0.759	1.600-3.452
TST1	0.868-0.883	0.939	0.940	0.952	0.768	1.643-3.727

(N=852, UINT=User Interface, CINI= Continuous Investment Intention, CON= Confirmation, INT= Interactivity, INVI= Investor's Intention, PLF= Perceived Playfulness, PRL= Perceived Relatedness, USE= Perceived usefulness, TST= Trust)

DISCRIMINANT VALIDITY: HTMT RATIO OF CORRELATIONS (TABLE-2)

HETEROTRAIT-MONOTRAIT RATIO (HTMT) - MATRIX									
	CINI	CON	INTR	INVI	PLF	PRL	TST	UINT	USE
CINI									
CON	0.825								
INTR	0.745	0.756							
INVI	0.835	0.836	0.824						
PLF	0.671	0.666	0.702	0.755					
PRL	0.723	0.665	0.685	0.725	0.551				
TST	0.710	0.733	0.743	0.785	0.685	0.664			
UINT	0.709	0.723	0.747	0.808	0.727	0.705	0.779		
USE	0.720	0.734	0.761	0.826	0.724	0.718	0.773	0.781	

(N=852, UINT=User Interface, CINI= Continuous Investment Intention, CON= Confirmation, INT= Interactivity, INVI= Investor's Intention, PLF= Perceived Playfulness, PRL= Perceived Relatedness, USE= Perceived usefulness, TST= Trust)

FORNELL-LARCKER CRITERION VALIDITY (TABLE-3)

FORNELL-LARCKER CRITERION									
	CINI	CON	INTR	INVI	PLF	PRL	TST	UINT	USE
CINI	0.893								
CON	0.725	0.861							
INTR	0.657	0.671	0.906						
INVI	0.737	0.742	0.734	0.868					
PLF	0.603	0.599	0.636	0.687	0.854				
PRL	0.617	0.566	0.583	0.618	0.484	0.849			
TST	0.644	0.667	0.681	0.719	0.637	0.579	0.876		
UINT	-0.626	-0.640	-0.666	-0.721	-0.655	-0.597	-0.712	0.871	
USE	0.645	0.660	0.688	0.748	0.663	0.617	0.718	-0.765	0.871

(N=852, UINT=User Interface, CINI= Continuous Investment Intention, CON= Confirmation, INT= Interactivity, INVI= Investor's Intention, PLF= Perceived Playfulness, PRL= Perceived Relatedness, USE= Perceived usefulness, TST= Trust)

5. Statistical result:

5.1 Structural results findings:

The collected data is processed following PLS-SEM method, with the support of Smart PLS 4.0 software. All prerequisites in the structural model were scrutinised by means of the PLS-SEM technique, developed by (Hair J.J. and Sarstedt M. and Ringle C.M., 2019). In the 5000 bootstrap iterations, without altering the sign, we examine hypothesis (Henseler et al., 2015b). This approach is widely credited as being the most advanced and reliable procedure for working with both linear and non-normal distributions (Hair et al., 2011). Path analysis shows how seven variables strongly affect the strength to resist making firm illiquidity-driven investments. Bootstrap analysis provides following results: user interface (β=0.103, t=4.124, p=0.002), perceived relatedness (β=0.092, t=3.492, p=0.000), interactivity (β=0.184, t=5.480, p=0.000), perception of usefulness (β=0.294, t=4.756, p=0.000), confirmation (β=0.254, t=8.288, p=0.000), perceived trust (β=0.129, t=3.353, p=0.001), perceived playfulness (β=0.163, t=5.468, p=0.000) and intention of investors (β=0.733, t=31.446, p=0.000). The study has ample evidence to back each hypothesis and shows a massive impact of the predictor variables on behavioral intentions. So, H1, H2, H3, H4, H5, H6 and H7 are approved. Behavioral intention is expected to have a positive effect on continuous investment intention, and the result is shown to confirm this in Table 4. Thus, H8 should be investigated more thoroughly.

Bootstrapping Direct Effects (Table 4):

BOOTSTRAPPING DIRECT EFFECTS							
EFFECTS		STANDARD BOOTSTRAP RESULTS					
	ORIGINAL COEFFICIENT	MEAN VALUE	2.5%	T VALUE	P VALUES	97.5%	FINAL RESULT
CON -> INVI	0.254	0.255	0.196	8.288	0.000	0.316	Supported
INTR -> INVI	0.184	0.184	0.120	5.480	0.000	0.250	Supported
INVI -> CINI	0.737	0.738	0.689	31.446	0.000	0.780	Supported
PLF -> INVI	0.163	0.163	0.105	5.468	0.000	0.221	Supported
PRL -> INVI	0.092	0.094	0.042	3.492	0.000	0.147	Supported
TST -> INVI	0.129	0.128	0.056	3.353	0.001	0.207	Supported
UINT -> INVI	0.103	0.101	-0.011	4.124	0.002	0.207	Supported
USE -> INVI	0.294	0.292	0.166	4.756	0.000	0.406	Supported

Indirect effect: (Mediating variable: Investors intention)

The bootstrapping approach proposed by (Jose, 2016)was used to examine the mediating effects of investors' behavioural intentions. To do this, we used the two-stage method suggested by (Baron & Kenny, 1986). The bootstrapping analysis looked at how behavioural intention mediated the relationship between a criterion variable (investor's investment intention) and determinant variables (user interface, perceived relatedness, interactivity, perceived usefulness, confirmation, perceived trust, and perceived playfulness). To evaluate the direct relationship between predictor and criterion variables, six more paths were created in the PLS-SEM model. The results show that the predictor's indirect effect on continuous investment intention through behavioural intention was substantial. The PLS-SEM was then conducted at a 95% confidence level.

5.2 Artificial neural network (ANN) analysis:

With the help of SEM and Artificial Neural Networks (ANN), this study found factors that affect one's investment intentions. Although how structural equation modelling works a great deal as given in (Bhatt et al., 2024). But such a compensatory framework might also make matters worse: it just represents very simple views of the complex, highly nonlinear processes by which people form their perceptions. Meanwhile, SEM allows us to test whether or not the linear model assumptions are satisfying (Patel et al., 2024). In contrast, the non-compensatory model makes ANN capable of identifying both linear as well as non-linear interactions (Chan & Chong, 2012). Hence, regarding the network as an artificial neuron, it can replicate on a smaller scale some of those many different considerations which have to come into human decision making. However, whereas ANN is capable of capturing both linear and nonlinear interactions within the model, its "black box" nature handicaps it in hypothesis testing as well as prediction task (Priyadarshinee et al., 2017). This paper combines SEM and ANN with a hybrid approach to compensate for each method's weaknesses while expressing their merits. The method takes over the crucial variables that emerge from hypothesis testing in the first stage of SEM analysis to apply them to subsequent ANN analysis (Thomas et al., 2024). Through incremental learning, knowledge can be enhanced (Ooi et al., 2018). The artificial neural network learned input-output mappings could help control nonlinearity (Sim et al., 2014). The advantage of using artificial neural networks is that it can focus on things based on relative significance, while also allowing for the capture of all sorts linear and non-linear relationships that occur between predictors and an outcome variable. A neural network is a powerful predicting tool, often with clear demonstrated superiority over traditional regression methods (Sharma et al., 2016).

Result and validation of ANN:

An artificial neural network analysis was carried out using SPSS 25. The final model uses the input-layer and thus covers all the relevant factors identified in PLS-SEM research about the sustainable Consumer Advocacy. While a single hidden layer may be satisfactory to represent a continuous function (Sharma et al., 2016), in this study we used one hidden layer. All input values were normalized to be in the range (0, 1) (Liébana-Cabanillas et al., 2018). This study adopted the sigmod function in both of its hidden and output layers. We used the standard 10-fold cross-verification method to address overfitting problems. In this study, the data was divided into 10% for testing and 90% training (Leong, Hew, Ooi, & Lin, 2019). The final output layer was investment intention; among the characteristics measured in the input layers were terminal screen design, perceived relatedness, interaction, perceived usefulness, confirmation, perceived trust, and perceived enjoyment etc. (Appendix- figure 3).

Table 05 shows that RMSE values of both the training and testing data are almost the same, proving that it has drawn an accurate ANN model for predicting an individual 's behavior based on its antecedents. A reduction in RMSE (Root Mean Square Error) demonstrates that the model is better aligned with data and therefore has more assumed accuracy. Moreover, a sensitivity analysis was conducted and showed the normalized variable importance (in %) for each input variable based on its relative ranking across every generation of ANN models. Confirmation is the most important predictor of desire to invest in online mutual funds, following with usefulness, while user interface has a lesser impact, following with perceived relatedness, according to the normalised variable importance. (Appendix- figure 3)

K fold ANN validation & independent variable importance (Table-5)

	Training			**Testing**			**Relative importance**						
Sr. ANN	SAMPLE	SSE	RMSE	SAMLE	SSE	RMSE	TST	USE	CON	PLF	UINT	INT	PRL
ANN1	766	5.162	0.0821	86	0.603	0.0837	0.129	0.117	0.214	0.132	0.05	0.194	0.104
ANN2	774	5.114	0.0813	78	0.411	0.0726	0.154	0.191	0.156	0.099	0.092	0.233	0.074
ANN3	758	5.299	0.0836	94	0.624	0.0814	0.109	0.205	0.292	0.117	0.051	0.229	0.032
ANN4	751	5.452	0.0852	101	0.52	0.0718	0.119	0.284	0.196	0.134	0.076	0.13	0.072
ANN5	763	5.531	0.0851	89	0.557	0.0791	0.156	0.243	0.227	0.142	0.065	0.188	0.095
ANN6	765	6.832	0.0945	87	0.533	0.0783	0.214	0.152	0.26	0.167	0.076	0.211	0.071
ANN7	767	5.246	0.0827	85	0.468	0.0742	0.125	0.148	0.259	0.15	0.079	0.196	0.083
ANN8	765	5.621	0.0857	87	0.395	0.0674	0.153	0.137	0.186	0.164	0.087	0.213	0.069
ANN9	760	6.792	0.0945	92	0.437	0.0689	0.137	0.252	0.179	0.143	0.066	0.194	0.092
ANN10	759	5.128	0.0821	93	0.538	0.076	0.126	0.272	0.174	0.112	0.098	0.151	0.087
M			0.08568			0.07534	0.1422	0.2001	0.2143	0.136	0.074	0.1939	0.0779
NI (In %)							66.36	93.37	100	63.46	34.53	90.48	36.35
#							4	2	1	5	7	3	6

(Total N = 852, k-fold ANN analysis result using IBM SPSS , ANN output layer variable: CINI (continuous investment intention), Input layer: TST (trust), USE(perceived usefulness), CON (confirmation), PLF (perceived playfulness), UINT (user interface), INT (interactivity), PRL (perceived relatedness); Sum of squares of errors(SSE); Root mean square error (RMSE); Arithmetic mean (M); Normalized importance percentile (NI); Final mean importance rank of independent variable (#); Artificial neural network model (R2) = 1 – (RMSE/s2y) = 81.20 %)

5.3 Necessary condition analysis (NCA):

The multi-stage structural equation modelling-necessary condition analysis (SEM-NCA) has significant advantages in terms of current research However, it does need to authenticate and significance the evidence on relationships. PLS-SEM provides sufficient evidence in the examination of hypotheses given that Necessary Condition Analysis reveals the conditions necessary for a theory, it forges an effective tool for theory development. (Dul et al., 2020) also studies behaviour intention of the individual. This research sought to identify the peer groups of financial advisers for each of these seven variables in turn and gave examples from live investment websites. This study also looked at the effect of many factors, including financial education, financial health, the bother factor, risk aversion, social influences, perceptions of regulatory variables and historical biases in individual behaviour. Table 6 gives the magnitude of effects. CE-FDH, a commonplace acronym for ceiling envelopment CEFDH, is a line of ceiling with absolute timing.
The basic idea is that all necessary terms to achieve one hundred percent intention are on the diagonal and off the main course. The threshold values of the necessary conditions in achieving a certain behavioral intention were found by using the decision strategy. The parameters to attain a behavioral intention of one hundred percent are shown in the table below (Table-6, Table-7). The minimum requirements include user interface (99.061%), perceived relatedness (94.601%), interaction (73.239%), perceived usefulness (99.531%), confirmation (99.178%), perceived trust (99.413%), and perceived playfulness (87.793%).

CE-FDH (Ceiling envelopment free disposal hull) (Table-6)

CE-FDH			
	Original effect size	95.0%	Permutation p value
CON	0.243	0.091	0.000
INTR	0.208	0.087	0.000
PLF	0.121	0.068	0.000
PRL	0.124	0.087	0.000
TST	0.122	0.066	0.000
UINT	0.193	0.108	0.000
USE	0.157	0.069	0.000

Bottleneck percentile (Table 07)

Bottleneck percentile								
	INVI	CON	INTR	PLF	PRL	TST	UINT	USE
0.000%	-2.280	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10.000%	-1.861	0.117	0.235	0.000	0.000	0.000	0.469	0.117
20.000%	-1.442	0.117	0.235	0.235	0.000	0.352	0.469	0.352
30.000%	-1.023	0.587	1.174	0.235	0.000	0.587	0.469	1.291
40.000%	-0.605	0.587	1.174	0.235	0.000	0.587	0.469	2.700
50.000%	-0.186	0.587	1.174	0.235	0.235	0.587	0.469	2.700
60.000%	0.233	0.587	1.174	0.235	0.235	0.587	0.469	2.700
70.000%	0.652	17.488	11.385	0.235	0.704	0.587	0.469	2.700
80.000%	1.071	32.981	17.723	10.681	2.113	4.930	2.465	11.033
90.000%	1.489	47.535	34.742	43.897	49.178	36.502	58.216	45.070
100.000%	1.908	99.178	73.239	87.793	94.601	99.413	99.061	99.531

6. Discussion and Conclusions:

6.1 statistical outcomes:

Reflected by SEM-ANN-NCA, the user interface is the most important factor influencing the continued investment intention of investors. Its influence upon the first user experience, thereby determining the usability and overall corporate attractiveness of the platform. Though valuing the user interface only 34.53 – ANN reasoning with a little better quality in life than it does elsewhere in nature (0.103, p=0.002) Sure evidence from path coefficients showed that a good 'user interface' can make people happy and helps them in making decisions as investors and savers over time." Organizations must thus make user-centred design a top priority. They have to ensure that the layout, navigation and visual elements are intuitive and compelling. Regular updates, together with usability testing, must be top priority to ensure smooth user interaction with the application and minimize any resistance in the investment process at all costs. Perceived relatedness of offered content retrieves, which involves such applications as influencing in fact on future investment actions nearly in parallel. For investors, a service that provides personalized and relevant recommendations in line with such investor needs is often easier to access. The path coefficient is 0.092, paired though weakly significant in ANN by 36.35%, which demonstrates that "content curation" is indispensable. Online mutual fund platforms must make use of artificial intelligence and big data to provide personalized recommendations, insights and market analysis for every shareholder. Application response to user queries and adaptability in

the face of user actions, was found to be a significant predictor of investment intentions both SEM (0.184) and ANN (90.48%). And, this discovery is very important, especially in financial services where market volatility demands instant response capabilities. To add real-time communication capabilities, including immediate feedback on investments made by your client, Call, live customer service, and latest market information. Platforms have to abandon waiting for people to push the mouse, and the need is much more now that a downward movement will be needed sooner.
The parameter, Perceived usefulness is one of the most influential factors and was both significant in linear model and non-linear (SEM: 0.294, ANN: 93.37%). The user's appraisal of value added for investment operations has a direct impact on whether they will continue to use this platform. Surprisingly, it coincides with classical TAM research, which establishes that perceived usefulness is the primary determinant for technology adoption. The confirmation construct, representing whether what users expect from the system is actually the case, influences individual investment behavior greatly (SEM: 0.254, ANN: 100%). More satisfied users who find that their expectations are met tend to keep on investing.
Trust significantly affects ongoing investment sentiment (SEM: 0.129, ANN: 66.36%). Trust is a crucial ingredient in financial services, especially online where clients attach great importance to keeping their data confidential and protected. Data security and privacy should receive their due emphasis at the websites of Internet mutual fund companies. Confidence scale used in sophisticated security protocols acquisition of certifications, providing precise privacy principles are all important means to build safety. To highlight these aspects in marketing communications may still confidence in consumers and solidify the engagement of customers. Users' subjective enjoyment of their platform experience-the perceived playfulness-contributes materially to its outcomes (SEM: 0.163, ANN: 63.46%). All this research demonstrates that user satisfaction, often considered unimportant by most Westerners in a financial situation, may lead to additional engagement and greater lifelong usage because enjoyment is derived from using the service.
Necessary Condition Analysis declares certain variables, like USE, TST, & CON are essential for the formation of continuous investment intentions. Without these basis conditions in place, despite of whatever other aspect you can think about things with man's wisdom will be of no use at all. While the ANN model based on artificial neural networks has a high predictive accuracy, non-linear interactions play an important part in understanding investment behaviour. Its use helps to reveal hidden patterns in user behaviour, providing insights one cannot get from traditional linear models like structural equation modelling (SEM). The strong relative relevance of confirmation and perceived usefulness just show that they play a leading role in predicting continued investment intentions.

7. Theoretical Contribution:

This study cartels TAM, ISSM and ECM to provide a comprehensive framework encompassing technology adoption and user satisfaction in online financial services. This multi-model approach increases a concrete understanding of the current investment goals. The study provides a new methodological approach that brings together Structural Equation Modelling (SEM) to test hypotheses or theories, Artificial Neural Networks (ANN) to make predictions and Necessary Condition Analysis (NCA) to determine conditions that are necessary to achieve a particular outcome. This multi-phase study has assisted in predicting accuracy using ANN and NCA key for the management decision making. This study extends prior studies by zeroing in on the post adoption phase and specifically on the factors influencing continuing investment intention. This article addresses the long-term user engagement which is a sustainability key for providers of digital financial services, whereas prior studies mainly considered early adoption. In providing for trust and perceived fun to the openness of TAM, the research also expands the traditional focuses of TAM and ISSM models. This new amalgamation is especially relevant to digital platforms, with trust and user satisfaction being critical to their continued engagement and loyalty. It provides valuable insights for scholars and practitioners related to fintech and investment services by including a user interface, trust, usefulness, and interaction in this approach.

8. Managerial Implication:

The findings indicate that user interface and interaction have a significant effect on continued investment intention. Finance companies need to create eye-catching, user-friendly, and interactive online mutual fund applications that will increase user engagement significantly. So, making it easy to use, and quickly reactive will grant them happiness and invest. The importance of perceived relatedness on satisfaction and retention rates indicates that relevant, personalized content aligned with users' investment decisions enhance these outcomes. Organisations must provide data driven personalised recommendations and alerts on news relevant to user investment plans. Trust becomes an essential driver for future investment deliberation. A solid security framework with proper guidelines and reliable customer support trust in the users. Marketing should focus on how the platform protects user data and creates a trustworthy environment for investing. According to the study, continuous investment activity is influenced by the perceived usefulness and the confirmed expectations. By providing efficient portfolio management tools along with reliable performance that matches or exceeds user expectations, long-term client loyalty will be enhanced. Playfulness is the perception that increases the motive of repeated investment in task. If investing apps with user-friendly unique features, gamification, great design, ensure unique user experiences resulted in frequent use.

9. Limitation and future research:

Less than ideal conditions for the current research mean that we have new avenues to open. The learning may not apply to other cultures and markets with a regional focus on Indian investors. The non-probability purposive sampling approach may not provide a complete picture of mutual fund investors, and the cross-sectional methodology limits insight into changing behaviours. External economic factors such as regulatory changes and market fluctuations influence long-continued investment intention which is not addressed in the study. Longitudinal studies with follow-ups to assess behavioural change over multiple time points, expansion of the global marketplace, and the inclusion of a large spectrum of external determinants should address these limitations. Studying the impacts of blockchain and AI and the behaviours of users segmented by various demographics will result in better applicability of the outcomes and assist in building enhanced user-centred mutual fund systems.

Declarations: All authors declare that they have no conflicts of interest.

Appendix:

Demographic sample characteristics (Table 1)

Category	Types of respondent	Frequency	Percentage
	Male	575	67.5
Gender	Female	277	32.5
	<200000	293	34.4
Income	200000-500000	143	16.8
	500001-1000000	243	28.5
	>1000000	173	20.3
	<25	349	41.0
	26-30	270	31.7
Age	31-35	113	13.3
	>36	120	14.1
	<12	86	10.1
Investors experience	12-18	226	26.5
	18-24	388	45.5
	>24	152	17.8
	Total	**852**	**100**

Measurement of Variable (Table 2)

Variable	Definition	Statement	Adopted and modified from
User Interface (UINT)	User Interface quality reflects the design and usability of the application's interface.	**UINT1:** The user interface of the application is attractive. **UINT2:** The layout of the application is well-organized. **UINT3:** The interface design makes the application easy to use. **UINT4:** The visual elements of the application are appealing.	(Hwang & Kim, 2007)
Perceived relatedness (PRL)	Perceived Relatedness reflects the extent to which users feel a sense of connection with the application.	PRL1: The application provides content that is relevant to my investment interests. PRL2: The recommendations I receive are personalized and useful. PRL3: The application helps me feel more engaged in the investment community.	(Deci & Ryan, 2000)

Interactivity (INTR)	Interactivity measures the degree to which the application allows user interaction.	**INTR1**: The application allows me to interact with real-time investment data. **INTR2**: I can easily get feedback from the application when performing tasks. **INTR3**: The application responds promptly to my actions. **INTR4**: The interactivity of the application enhances my overall experience.	(Liu & Shrum, 2002)
Perceived Usefulness (USE)	Perceived usefulness is a key construct in TAM and reflects how much the application improves users' investment outcomes.	**USE1**: Using the online mutual fund application enhances my investment performance. **USE2**: The application improves my effectiveness in managing my investments. **USE3**: The system allows me to make better investment decisions. **USE4**: Using the application increases my control over my financial portfolio **USE5:** It helps to manage capabilities to investment	(Venkatesh & Davis, 2000)
Confirmation (CON)	Confirmation reflects the degree to which the application meets users' initial expectations.	**CON1:** The application performs as well as I expected. **CON2:** The features of the application match what I anticipated. **CON3:** The application's performance is consistent with my expectations. **CON4:** The application performs the functions I expected it to when I started using it.	(Bhattacherjee, 2001b)
Perceived Trust (TST)	Perceived Trust refers to the degree to which users feel confident in the security, privacy, and reliability of the online mutual fund application.	**TST1**: I trust transactions happening through online mutual fund. **TST2**: I trust that the providers of mutual fund app will not divulge any of my information to third party **TST3**: I believe investment in mutual fund keeps customers' interests best in mind	(Grabner-Kräuter & Kaluscha, 2003)

		TST4: I believe application through which investment in Mutual fund done, keeps its promises and commitments **TST5**: I believe that in case of any issue the service provider will provide me assistance **TST6**: The application has a good reputation for protecting user data.	
Perceived Playfulness (PLF)	Perceived Playfulness measures the degree to which users find the application enjoyable and engaging, beyond its functional utility.	**PLF1:** I find using this application to be fun. **PLF2:** The application is enjoyable to use. **PLF3:** I feel playful when interacting with the application. **PLF4:** The application holds my attention because it is entertaining.	(Moon & Kim, 2001)
Investor's Intention (INVI)	It refers to the user's intention to continue using the online mutual fund application for future investments	**INVI1**: There is a good chance that I will put money into a mutual fund. **INVI2**: I would share positivity about investment in mutual fund to other. **INVI3**: Willingness to invest Mutual fund is high. **INVI4**: I am likely to recommend this application to others who are looking to invest in mutual funds	(Bhattacherjee, 2001b)
Continuous Investment Intention (CINI)		**CINI1**: I would like to invest in Mutual fund frequently **CINI2**: I would encourage my friend and family too, to invest in Mutual fund **CINI3**: I would like to invest in mutual fund regularly	(Bhattacherjee, 2001b)

Homogeneity of variance test (Table 3)

Test of Homogeneity of Variances				
	Levene Statistic	**df1**	**df2**	**Sig.**
INVI	**0.269**	**3**	**848**	**0.848**
CINI	**0.743**	**3**	**848**	**0.527**

Tests of Normality						
	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CINI	.141	852	.000	.946	852	.000
INVI	.107	852	.000	.953	852	.000
a. Lilliefors Significance Correction						

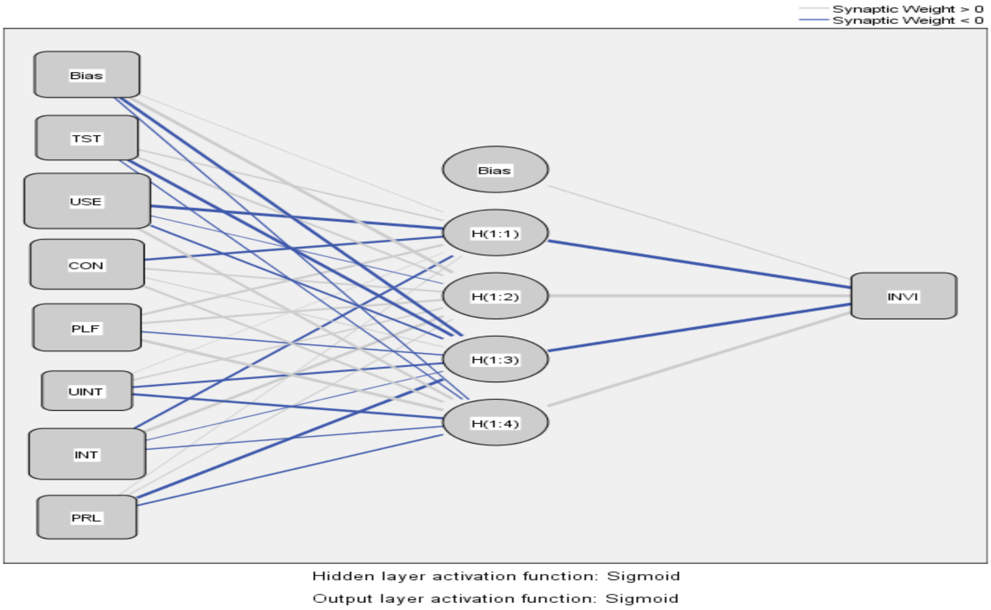

Figure:3

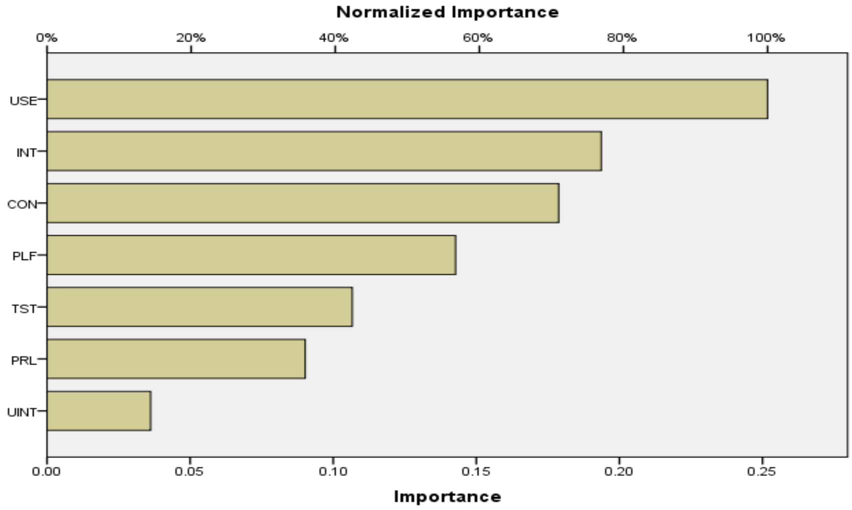

Figure:4

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