STUDY OF BEHAVIOURAL INVESTMENT IN INDIA

by

Tushar Sood
M.Tech

DISSERTATION
Presented to the Swiss School of Business and Management Geneva
In Partial Fulfillment
Of the Requirements
For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

January 2025

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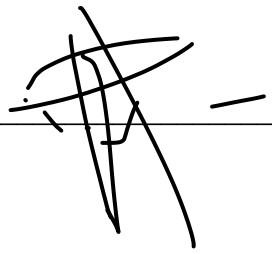

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DECLARATION

I hereby declare that the thesis entitled "Study of Behavioural Investment in INDIA " submitted to SSBM, Geneva for the award of degree of Global Doctor of Business Administration is my original research work. This thesis or any part thereof has not been submitted partially or fully for the fulfillment of any degree of discipline in any other University/Institution.

(TUSHAR SOOD)

Dedication

I would like to dedicate my thesis to my father, Dr Inderjeet Singh Sood, and my mother, Mrs Nutan Sood, for their relentless love, support, and guidance. This constant motivation and support are the main pillar of my academic success. They helped me shape up my goals and vision in life.

I would like to share my respect and love for my wife, Neha Sood, for the countless efforts she has put to keep me motivated throughout my DBA journey she has showered tremendous patience and faith on me when I needed the desired push. Her strong belief in me and my aspirations helped me to cross the obstacles that once seemed impossible to navigate. I would have missed most of my milestone if I didn't had her motivation and support.

I would also like to show my gratitude towards my lovely children, Master Hardik Sood, and Ms Shanaya Sood. Their endless 'What's and Why's' helped me innovate in dull times. They are my inspiration towards revision and perfection. Their enthusiasm and never giving up attitude has kept me on my toes during this journey.

I would also like to extend my deepest respect and appreciation to my guide Dr Kishore Kunal. His experience and constant review of my work has helped me correct my course many times. His unique ability to highlight novelty and push towards thinking big has kept me explore unknown territories. His supervision and guidance was what helped me the most throughout my DBA.

I also extend my heartfelt gratitude to my managers and friends for their constant motivation, support, and helpful advice. Their faith in me motivates me, and their insights and understanding have enriched my research.

Acknowledgements

I would like to sincerely acknowledge and thank my guide Dr. Kishore Kunal for helping me understand importance of DBA and its each phase. This thesis has been mentored and enriched by his knowledge and guidance.

I would like to show my humble gratitude to my friends, colleagues and the Upgrad team for keeping me informed on market, sharing information and program updates along with nudges on timeline. I would like to thank SSBM online trainers, Dr. Mario Silic, for his constant encouragement and assistance. Their insights and contributions have significantly helped me write my research and shape it well.

ABSTRACT
STUDY OF BEHAVIOURAL INVESTMENT IN INDIA

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2025

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The rapid evolution of investment markets and it's increasing complexity especially with decision-making requires innovative approaches to optimise investment outcomes. While traditional investment systems rely on centralised data repositories and decision-making processes, these approaches often suffer from data silos, privacy concerns, and information asymmetry.

Federated investment, a decentralised & distributed framework that leverages modern AI technologies, offers a promising solution to the challenge of privacy-preserving investment decision-making. Federated Investments can enhance investment decision-making by implementing the concept of collaborative knowledge sharing.

In my research, I investigate the potential of Federated Machine Learning to enhance investment decision-making. I intend to explore the need and advantages or disadvantages of implementing Federated Investments Decision Making (FIDM), a framework where collaborative learning occurs without sending investors behavioural data. In my research I also surface the urgent need for data security, privacy, and fairness in predictions of financial news distribution, aiming to contribute to a more efficient, equitable, and secure investment ecosystem.

In my research, I study the impact of finfluencers on investors' behaviour in INDIA. The massive adoption of digital platforms and Generative Video Content motivates financial gurus to spread asymmetric market news, leading to wrong and incorrect perceptions about market conditions. This causes investors to make unjustified investment decisions leading to losses and, hence averting future investments.

In conclusion, we can see how FIDM can preserve the privacy of investment portfolios at the same time implement market news filtering related to the behaviour of investors.

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INTRODUCTION

1.1 Introduction

INDIA has a growing economy, and its vibrant capital markets have made it an attractive destination for investors worldwide. The country's vast population, growing middle class, and favourable government policies have fueled significant growth in various sectors, including technology, healthcare, and manufacturing.

(Raj, 1970) discusses that, as the INDIAN economy grows, it is faced with the problem of enhancing its savings rate and planning towards improving economic growth. Despite INDIA's considerable progress in recent decades, its savings rate, although around 5%, is inferior to that of other comparable industrialized economies. Highlighting this rate is important to fund and improve expenditures in infrastructure, education, and technology, which are vital for the INDIAN economy. Moreover, India's capital-output ratio, which is also comparatively low, signifies the necessity of *enhancing investment efficiency* so that economic output can be optimized and better benefits can be reaped. INDIAN policymakers should prioritize rewarding savings and promote investments in high-return areas to expedite India's economic advancement, at the same time reducing the associated risks.

(Mohapatra and Ghosh, 2024, 2023) emphasizes the impact of digitalization and growth of the retail sector which have significantly changed INDIA’s financial landscape. This highlights the need for a strong framework for protecting investors. This study investigates the subtle relationship between investor education and its protection, aligning with the Indian education setup. It highlights the governing role to be played by government, regulators, and financial institutions. The rise of Fintech and the increased digitization of the world has made investments more accessible, which means new ways of

protecting the investors money and ensuring that the investors interests are looked after. This report evaluates existing frameworks and highlights the need for a robust and complaint resolution process, along with "class-oriented" approach to financial education, complementing the existing *National Strategy on Financial Education (NSFE).* This report discusses the important initial steps, this include creating a centralized grievance redressal system and creating a more secure regulatory framework that has strong cybersecurity measures. The report stresses that the investor protection requires a collective approach, with both regulators and investors sharing responsibilities for vigilance and understanding in this ever-growing digital world.

(Dr. Namrata Gain; Narendra Verma, n.d.) studies deal with changes in the investment patterns of India, which are prompted by the country's economic reforms, technological progress, and growth in the investor's independence. With the application of the multi-method approach, the research examines how demographic, behavioral, and other external factors affect investments by the Indian population. The main ones indicate age-wise difference in risk taking ability and income-based portfolio diversification. The study demonstrates how behavioral biases, such as herding and overconfidence, affect investment decisions. The study fills the gap in investment behavior in this region by stressing the importance of developing suitable economic education and stronger regulations to protect investors and achieve a more balanced and stable economic market in INDIA.

Indian investors utilize two methods of understanding investment: technical analysis and fundamental analysis. Both methods give them info about the market directions, how the businesses are doing and investment possibilities. First, fundamental analysis. It determines how much a business is worth based on its finances, industry, and the economy. Some of these factors include revenue and earnings, competition, and debt.

Fundamental analysts would reason that the true worth of a business lies in how well it performs financially and its future expectations. On the other hand, technical analysis uses price charts, graphs and other patters to understand how the price is likely to change in the future. This strategy assumes that all available information regarding the business is factored into its market price and that examining previously used price patterns will aid in spotting trends which can be the basis of trade. When making decisions, technical analysts use several tools which include support and resistance levels, moving averages, and the relative strength index (RSI).

As Warren Buffet once said, "*It's far better to buy a wonderful company at a fair price than a fair company at a wonderful price*". However, modern-day investments suffer from a *lack of information and have lots of biases*. One way to tackle these problems is to *invest in collective intelligence*. INDIA does not have structured and polished investment education, and because of this, a lot of investors rely on advisors and agents to make the right investment decisions. In recent times *"The Securities and Exchange Board of India"* (SEBI) and Banks in INDIA have made cautious attempts to spread awareness about the risks associated with investments. Investors may not always get desired returns and often lose lots of hard-earned money.

(Shamim and Azam, 2024) talks about the impact of social media influencers on viewers. With the increased viewership of video content in INDIA over YouTube and other channels, there is an increased count of online educators charging a nominal fee for investment suggestions, tricks, and tips. These finfluencers are recognised as a concern by SEBI in the following article ("As Finfluencers Grow, Can Sebi's Regulations Snap Investors Out Of Their Fantasy World?," n.d.). Such content targets the "*Urge to Buy Impulsively"* (UBI) behaviour of an investor which lacks *fundamental analysis* by an investor.

In my thesis, I study such influencers' content, which is posted online and investigate the direct and indirect recommendations to buy or sell particular investments. (Standard, 2024) this article raises serious concerns about finfluencers and quotes that *"Finfluencers often operate outside the realm of traditional financial advisors. They may not be formally qualified or registered with any regulatory body. Additionally, their advice can be clouded by conflicts of interest, particularly if they're working on a commission basis or promoting specific products."* However, as of today, over 2000 investors share their thoughts and run their education series online. It is also important to note that many times, celebrities are also involved in educating certain investments and hence are the major cause of influencing investors towards a particular asset or company.

Online Social Media Information (SMI) is not restricted to only investment. However, it also contains recommendations on various types of trading and other types of financial recommendations. Although, Finance and Investments are closely related following are the similarities and differences:

Table 1: Comparison between Finance and Investment

Property	**Finance**	**Investments**
Allocation of Resources	Involves allocation of resources, primary capital to achieve specific goals.	
	Focus is on allocation for personal or other business purposes	Focus is only on generating profitable returns
Risk and Returns	Manage risks to optimize returns	
Time Value of Money	Consider Time Value of Money and recognizes that value of money can appreciate or depreciate in future	

Markets	Rely on financial markets to facilitate the exchange of funds and assets like stocks, bonds, currencies etc.	
Financial Analysis	Require financial analysis to assess the potential risks and rewards of various opportunities. This involves evaluating financial statements, market trends and economic indicators	
Goal Oriented	Goals might include Savings for retirement, purchasing a home or starting a new business	Goals might be capital appreciation, income generation or risk diversification

In essence, finance provides the framework for managing money, while investment is a specific application of finance focused on growing wealth through the purchase of assets. In an INDIAN society, there are a couple of other biases created due to which investment decisions are impacted. Some of them are herding behaviour, anchoring behaviour, overconfidence, uninformed market predictions market bias etc.

As INDIA prepares itself for a stronger Digital India, several challenges are lying ahead. (Malhotra, 2024) talks about how technology will become the foundation pillar of new-age digital INDIA. Between 2020 and 2030, there will be a lot of emphasis and the emergence of Digital Platforms (DP). These DP's can be accessed by citizens over mobile, computer or any other digital platform, hence improving the reachability of digital evolution. As the government prepares for such hi-tech platforms, data privacy is of utmost importance. Lots of governments across the globe are implementing data governance policies. Some of them are:

Table 2: Potential Data Security frameworks to follow

Domain	Description

Regulations	Regulations Protecting Movement of sensitive data: GDPR (Europe), CCPA (California), PIPEDA (Canada), LGPD (Brazil), PDPL (Argentina), KVKK (Turkey), POPI (South Africa), FSS (Russia), CDPR (China), PDPB (India), PIPA (Korea), APPI (Japan), PDP (Indonesia), PDPA (Singapore), APP (Australia) These regulations restrict data from being cross engineered for centralized model training
User Preference	Any information (passwords, digital banking cards, etc.) fed into mobile devices is not expected to be stored on external servers
Data Volume	It is neither feasible nor economic to collect all the data (due to, limitations on internet bandwidth or communication efficiency)

These digital platforms mostly sit on cloud or edge computers and can be accessed from any demography which is connected to the internet. (Lahiri^1 and Ahmad, 2024) also highlights how countries embracing technology for the benefit of citizens have recorded radical change in all aspects that trigger higher GDP growth.

As INDIA observes the strong trajectory of digital platform growth, there is an urgent need for *"Responsible regulations"*. (De' et al., 2024) states that such policies are in confused states and need lots of relevant reforms in order to make them useful for citizens.

In my research, I explore **Federated Machine Learning (FML)**, which focuses on keeping the investment data local to the user but still offers the benefits of collaborative investment intelligence.

1.2 Research Problem

The abundance of investment information disseminated through various regulated and unregulated channels, including news media, social media, and self-proclaimed "experts," creates a significant challenge for investors seeking reliable and trustworthy sources. This information overload often leads to **misinformation and disinformation**, which can harm investment decisions.

(Mohapatra and Ghosh, 2023) highlights that INDIA has, in the last few years, experienced a sea change in its investment universe – a sea change that has been driven by digitalization and the growth of the retail sector. Because new opportunities for investment are now more available than before, there is also a greater need for adequate protection of investors. They also calling for a more dynamic model, recognizing the shortcomings of the existing investor protection framework when trying to protect investors in the era of digitalization and other emerging fintech innovations.

(Kandpal and Mehrotra, 2018) indicates how individuals' behaviour is imperative to the study of investment patterns. There is no gainsaying that the Investment decisions in INDIA are sometimes quite frivolous due to ignorance and absence of faith in the information put forth. The majority of the financial decision making is based on perception, rumors, past returns and planning is absent.

(Kumar and Goyal, 2016) This study looked at the relationship between the rationality and biases in the decision making process of an average Indian Investor. The results from the structural path analysis indicate that a standard overconfidence, and herding behavior, particularly in men, are some of the biases that disrupt the rational decision making process in the investment domain. These findings point to the necessity of understanding these biases and their mitigation to investment outcomes.

According to (Subash, 2012), there is considerable volatility in the Indian financial markets since the global financial crisis of 2008. This research focusses on the psychological biases present in the investment decisions made by Indian investors. Using a sample of 92 investors stratified by experience and age, the effects of specific behavioral biases like overconfidence, representativeness, herding, and hindsight bias were assessed. The results showed that there are differences between young and experienced investors. The younger category was more prone to gambler's fallcy, placing a greater emphasis on Anchoring and Hindsight biases than the older category that had a much subtler grasp of these psychological traps. It is crucial to acknowledge that behavioral biases exist among investors and that they should be taken into account when constructing investment portfolios, particularly among younger participants of the Indian market.

(Wang et al., 2017) dentifies that in particular countries, the propagation of misinformation can be utilized in order to distort the market. With the advancement of the Information and Communication Technology in India, the amount of investment spending, as well as the dissemination of false information, will increase.

My investigations led me towards some issues like:

1. Determining what particular investment(s) is/are appropriate for an investor in accordance with their investment tendencies.
2. Establishing relevant investment information subjects that are least influenced or biased
3. Sifting through new information on market movements, which may be suitable for the investor based on their behavioral patterns and habits

1.3 Purpose of Research

According to (Ekmefjord et al., 2022), they created a new framework for federated machine learning, which they have called FEDn. FEDn is expected to be thin, easy to use, and powerful, operating on multiple endpoints and with different libraries of machine learning. The authors put FEDn to field tests—many users and megamodels—and demonstrated that it works, confirming its performance for various workloads. They feel that FEDn will be useful in production and for research in federated learning due to its ability to resolve complicated issues as well as its comprehensive design.

(Voltaire Edoh, 2022) explored the promise of identifying market manipulation, especially spoofing, with a federated approach to training models. However, further work remains to be done to determine its potential for other forms of manipulations and the differences seen in the various areas of federated learning frameworks.

As indicated by (Mohapatra and Ghosh, 2023), studies are required to focus on the factors that shape the adoption of AI-powered investment solutions in the Indian context, such as the perceptions and reliance of investors on domestic technology providers and the existing regulatory framework.

According to (Gopali and Shetty, 2020) , we are in a position to benefit greatly with the digital boom along with the increased economic growth (5-6%) that we are currently experiencing when compared to the average growth around the world. Key drivers of the Indian market are: Jan Dhan Aadhar Mobile (JAM) Trinity, Digital India, and post demonetisation. The high-net-worth individual (HNWI) end of the market is covered by financial institutions, whilst the investing needs of the emerging middle class are yet to be met. Whilst financial institutions target HNWIs, the advisors are reluctant to onboard these young investors as they have a low surplus to invest as compared to older generation clients. Artificial Intelligence is also a prediction machine, which by its very nature is

perfect for investment purposes, predicting portfolio performance, analysing risk and providing mass personalisation. Management fees have sustained the asset management industry for decades; therefore, a new mindset is required to rise above and beyond the current thinking. This shift requires a re-evaluation of traditional business models and a focus on building long-term relationships with a broader customer base. By embracing technological advancements and adopting a customer-centric approach, the financial sector can effectively tap into the immense potential of the Indian market and contribute to the country's economic growth.

(Mou, 2019) highlights a global race to develop and implement AI, emphasizing its potential to drive economic growth across sectors like energy, healthcare, education, and manufacturing. While recognizing the potential advantages for developing economies, it also highlights one fundamental issue: there is a large gap here. Although the do stand to gain from AI, developing countries such as India have attracted only a small proportion of AI investments. This situation emphasizes the fact that there should be more investments in AI development and research in India if the benefits of this advanced technology are to be fully harnessed.

The work of (AbdulRahman et al., 2020) proposes a new direction for the use of AI/ML in the financial sector. It addresses the salient issue of privacy by applying Federated Learning (FL). Indeed, FL addresses issues of data security and privacy for individual investors by allowing collaborative modeling without direct access to the investors' data. This decentralized method ensures that AI/ML investments and portfolio decision tools such as optimized investment portfolios, risk management, and advanced investment forecasting use better quality AI/ML models. At the same time, these models can take greater risks with their investments. But there are some boundaries that should be set, which the current analysis has failed to address. While we do acknowledge that the age

and the investment horizon approaches make good sense, income, education, and whether the investor is single or married will help to paint a clearer picture. Additionally, the role that finfluencer content plays in the behavior of the investors is very important, yet this study did not include that. This is an area that requires additional study. Other areas that require further research include how FL may interact with other strengthening technology like blockchain. How can these be combined to improve confidence in data security and privacy within the finance industry? By identifying these issues, setting out to address them, and forming a set of new researches to be conducted, the potential exists to use AI/ML more fully and safely to enhance and support better decision making for investors.

According to (Fenoglio et al., 2024) Federated Behavioural Planes (FBPs) are a unique conceptualization that allows for the visualizing and comprehending the interactions of users within Federated Learning (FL) systems. FBPs facilitate the consideration of client actions using two metrics: predictive performance and decision-making. By looking into these measures, FBPs categorize clients into groups based on shared behavioural patterns which helps to find clients exhibiting malicious or noisy activity. This strategy, along with Federated Behavioural Shields, increases the security of the FL systems that is necessary in trustless environments such as finance applications where privacy is important and the users must have control over the decentralized learning system.

This approach has potential relevance to the Indian context, where data privacy and security are significant concerns. Applying FBPs to analyze investor behaviour in a federated learning framework could help identify and mitigate risks associated with malicious actors or data poisoning attacks, ultimately enhancing the trustworthiness and reliability of AI-powered investment solutions in India.

In my research, I have investigated the framework using FML in investment decision-making. My aim is to subscribe to the market news and remove unwanted biases as part of data cleaning and hence pass it to the user if the news is found to align with the behavioural traits identified. In my research, investors are clustered based on their investment behaviours, and relevant FML models are loaded onto their devices for filtering news. My research work could help regulatory authorities like SEBI and regional governments to understand investment behaviour along with allowing the developer ecosystem to come up with good prescriptive models to recommend unbiased and prioritised investments coming directly from government policies. My research also enables uninformed investors to better understand investment opportunities and make decisions based on community intelligence.

(Arafeh et al., 2022) Federated Learning (FL) offers a promising approach to leveraging the power of distributed data while preserving user privacy. However, the success of FL hinges on addressing the challenge of non-independent and Identically Distributed (non-IID) data across participating devices. While existing research acknowledges this challenge, many approaches either fail to adequately address the fundamental nature of data heterogeneity or compromise the privacy guarantees of FL. This research introduces a novel approach to evaluating data distribution harmony among participants within an FL framework. Thus, this technique helps achieve a better-informed choice of participants by allowing an assessment of the compatibility of data from various devices, therefore helping combat the adverse effect of non-IID data. This approach represents a significant step toward unlocking the benefits of FL in business sectors with privacy concerns such as financial services where individual investors differ significantly in their investment objectives, risk tolerance, and experience.

When it comes to the traditional market equilibrium and the efficient-market hypothesis (Gajić et al., 2023) , there seems to be a gap in Indian investor behavior as it is in developed markets. Indian markets tend to exhibit behavioral biases, herd mentality, and have a significant presence of finfluencers. These characteristics deviate from the market efficiency assumptions. These factors suggest that Behavioral Investments (BI) is more prevalent than Efficient Market Hypothesis (EMH)..

Behavioural Investment (BI) outdates the **Efficient Market Hypothesis (EMH)** in principle. The emergence of finfluencers, however, gives rise to new challenges regarding these assumptions. EMH argues that all available information is accounted for in asset prices which causes it to be impossible to beat the market. Finfluencers are the new enhancement in the world of investing which have the ability to change tradition. Finfluencers create a ripple effect of exact influence and information sharing which halts efficient market hypothesis. The following supports this notion:

1.3.1 Information Asymmetry:

1.3.1.1 Selective Disclosure: ‘Finfluencers’ can learn information faster than the bulk population which may lead to information discrimination.

1.3.1.2 Biased Recommendations: Finfluencers may possess certain stocks or strategies which they can use to mislead individuals into believing their recommendation.

1.3.2 Herding Behaviour:

1.3.2.1 Social Proof: Finfluencers can, and in fact, do, have quite a number of followers and in turn, encourage investors to follow their suggestion without conducting their own research.

1.3.2.2 Market Bubbles: Investors' acceptance of the behavior can result in asset inflation and other collateral economic issues. The latter happens because purchase decisions are made on expectations instead of fundamental economic factors.

1.3.3 Emotional Decision-Making:

1.3.3.1 Fear of Missing Out (FOMO): This sense of urgency can be used by any Finfluencers to trick potential investors into making bad deals.

1.3.3.2 Anchoring Bias: A certain financial price target is set and advertised, this may aid financing influencers gain an advantage over personal investors.

1.3.4 Noise Trading:

1.3.4.1 Increased Volatility: All in all, increased market activity may lead to an increase in potential profits, Finfluencers can exploit this by motivating investors into high risk short term investing.

1.3.4.2 Misallocation of Capital: Factors that evoke this are emotional, not rational and therefore may lead to undeveloped spending of funds to less focused investments..

Table 3: Important Investment Considerations and Comparison between EMH and BI

Considerations	Efficient Market Hypothesis	Behavioural Investment
Access and Availability of Information	Controlled and many times sparse	Information flow is uniform and is filtered according to behaviour of investor
Fundamental Analysis	For any investment the information available allows investors to create a mind map about the investment and future trends	For any investment there is more stronger connection between investors behaviour and the investment opportunity

		hence the outcomes are well understood and more realistic
Technical Analysis	Current information flow and accessibility dictates the market and hence the value of investment	Information flow is uniform across the group of people having similar behaviour and hence indirectly considering the investment patterns
Uniformity	Investors exhibits a common pattern hence can be quantified easily like income, gender, education level, etc.	Behaviours of investors exhibit commonality and can vary in basic traits like gender, education level etc.
Investment Machines	Investors are considered as Machines being Rational all the time even if the decisions will incur in losses	Investors are categorized rational accordance to their behaviour of investing and not judged by the outcome
Emotions	Discourage and does not give any place to Human Emotions.	Emphasizes the correlation of emotional reactions with market events and asserts that emotions are the backbone of its theoretical framework
Investing Bubble	Heuristics such as cognitive anomaly an heard mentality greatly impacts EMH	BI is more individualistic and get control bubble anomalies in a better way

Contemporary Investing	Unmodified from over 50 years. Hence may suffer from irrational decision making in context of modern day investment strategies	Focuses on investors behaviour hence adapts proportional to maturity of the investor
Interdisciplinary Considerations	Characterized by optimism and emphasizes the positive outcomes of investing decision making	Combines elements from history, sociology, psychology and anthropology to predict a successful investment decision making

The proposed Federated investment framework is a Behavioural Framework expected to provide an alternative to the Efficient Market Hypothesis (EMH). This framework ensures the investors receive personalized investment proposals by allowing the information to flow towards the potential investors.

(Delcey, 2018) states that Eugene Fama's work done in the 1960s showed that markets exhibit different levels of efficiency, be it absolutely weak-form or strongly efficient strong-form. In the markets that exhibit strong form efficiency, all types of information whether public or private, is instantaneously incorporated within the prices. This makes it extremely difficult to persistently 'beat the market'. This idea runs contradicts basic investment strategies and emphasizes the need for information that is relevant and timely in this rapidly changing market. Eugene Fama's PhD dissertation in the 1960s spoke about three different forms of market efficiencies namely strong form, semi-strong form and weak form.

Table 4: Fama's forms for Market Efficiencies

Market Efficiency	Description
Strong Form	Information (public, personal, even confidential) contributes to stock pricing, and, therefore, does not enable investors to achieve a competitive advantage in investing processes.
Semi Strong Form	Stock prices reflect public financial information (announcements of listed companies, balanced sheets, assets etc.)
Weak Form	All past stock prices are integrated in current prices; therefore, they cannot be used for future predictions.

Constant high returns from the market are a function of non-uniform probabilistic distribution. This means that earnings are not always constant, and investment may result in losses. Also, across a group of investors for the same asset, someone will make money while others may incur a loss because they might have invested at different times and market conditions. If all of them invest at the same time their earnings will be the same for all. However, information and investment opportunities are always open for all, and anyone may forecast when to invest. This freedom provides an opportunity to predict and forecast future market conditions, hence affirming the returns. Investments are often related to how new information is perceived. Many investors rely on heuristics for processing investment information. Heuristics refers to acquiring knowledge or a desirable result by employing smart guesswork rather than specified formulas. (Ayaa et al., 2022) presents a paper which provides conceptual insights into the influence of heuristic techniques and cognitive biases in investment decision-making. Results from the conceptual analysis show that in recent times, investors, in their bid to minimise losses and maximize gains employ a range of heuristics which often lead to systematic errors in judgment.

(Sjøberg, 2011) highlights that behavioral finance has gained prominence in academic circles, its practical application in the Indian investment landscape remains relatively unexplored. Much like the Norwegian market, where the identification of 'behavioral' funds posed a challenge, Indian fund managers tend to seldom admit the use of behavioral finance strategies. This is a case study that will attempt to evaluate the performance of Indian mutual funds by looking more closely at their behavioral finance components, such as attention focus, value investment, and contrarian investments, and determine if these funds actually outperform the other existing funds in terms of risk adjusted returns. The research shall improve the understanding of the contribution of behavioral finance in the Indian scenario.

(Baviskar, 2024) This paper aims to assess the impact of finfluencers on the young Indian diaspora (ages 18 to 40) who consume financial content on Instagram and YouTube. This finfluencer analysis of the younger Indian audience examines the potential investment choices that this demographic is likely to make. The trustworthiness of the finfluencer advice and the content's effectiveness, as well as the regulation of the finfluencers, are all factors that can be investigated. Understanding the effect of finfluencers on young Indian investors will fill an important gap in the existing literature. This enables clients to be made more literate in finance so that they can make better choices, and also helps in formulating effective regulations regarding finfluencers in the Indian financial market.

(Symbiosis and Gandhi, 2024) This paper examines the role of finfluencers providing financial services and their possible impacts on the decision-making of clients, regarding their finances, as a link between behavioral economics and consumer behavior. The research studies the influence of social-media financial gurus on the financial choices of their followers and analyzes their financial proficiency, investment attitude, and the trustworthiness of their advice. Using an appropriate methodology, possibly one that uses

survey and data analysis, this research intends to identify which specific considerations and exigencies enable and motivate consumers in India to accept and depend on the recommendations of all and sundry that they encounter within the digital space. These findings will reveal the relevance of finfluencers in the country. This will, in turn, serve as a case study for developing strategies for financial literacy, investors' training, and regulations of finfluencers in India.

My research aims to study the Heuristics and cognitive biases induced through Finfluencers and other online media articles that impact investment decision-making. FML must use this knowledge and use it for filtering incoming news and market events to prescribe the right investment for an investor.

1.4 Significance of the Study

This research is of utmost importance, considering the advancement in technology and increasing society's maturity and understanding towards better financial stability. There is more than 90% of the investor's population who actively invest without relying on agents. However, they lack a proper framework to validate and get control of their investment without biases and involvement of middlemen making decisions for them. (Makwana, 2024) surfaces the intricate interplay between psychological factors and investment behaviour. The study highlights the need for a new generation framework for managing investment decision-making by reducing risks in investment decision-making. My research tries to use FML to reduce the risks in investments by avoiding influenced decision-making.

(Khurana, 2023; Sridharan, n.d.; Tejwani, 2023; Walia, n.d.) investigates the role of the Securities and Exchange Board of India (SEBI) in regulating the influence of "FinFluencers" on the Indian securities market. With growing social media, FinFluencers are gaining significant influence on investor behaviour. The increasing trend of social media use has stimulated the rise of 'FinFluencers', an emerging subgroup of influencers that affects how the public interacts and behaves towards the stock market. In reaction to this, this study attempts to explore the pros and cons brought forth by FinFluencers on the Indian securities market while also assessing how the Securities and Exchange Board of India (SEBI) attempts to deal with such challenges. According to Sridharan and , as some countries tend to overregulate the market, this article seeks to explore the advantages and disadvantages that might arise with lax regulations, in this case seeking to use India as a case study on the influence of promotion. The delay in implementing robust regulations in India, unlike countries like the US and Australia with established frameworks, leaves investors vulnerable. This necessitates a proactive approach by SEBI to adapt its strategies

and ensure investor protection in the face of the growing influence of social media on the securities market.

(Vadakkethil Somanathan Pillai and Parveen, 2024) introduces a multi-modal framework for combating fake news. The framework integrates diverse approaches to comprehensively analyze and understand fabricated information. Linguistic analysis examines the language and textual content of fake news articles, identifying misleading information, biased language, and sensationalized headlines. Social network monitoring tracks the spread of fake news through social media, identifying key actors and influencers involved in its dissemination. Visual assessment analyzes images and videos used to manipulate public perception, including the detection of doctored media. By combining these approaches, the framework aims to provide a more holistic understanding of fake news and its impact on society. However, in the world of privacy preserving investment domain a study is needed to analyze federated ML approaches.

(Singh and Kumar, 2024) paper aims to analyse the users' perception and acceptability of artificial intelligence (AI) in digital investment solutions using an extended "Technology Acceptance Model" (TAM). It also highlights practical implications highlighting the importance of improving ways to increase trust, reduce perceived risk and bring ease of use for technology. My research uses FML, which enables investor behaviours to be kept local hence creating a digital filter for investment decision-making.

(Khan et al., 2024; Rai et al., 2024) also emphasize on benefits of Machine Learning (ML) models for forecasting investment-related decisions. However, a generic ML model may not suit the varied investor population and their behaviours. My research showcases the use of FML to keep veracity in investment behaviours and at the same time learn from society by constantly improving news relevancy and investment recommendations.

(Abreha et al., 2022) focuses on the synergy between Edge Computing (EC) and Federated Learning (FL). While EC brings cloud services closer to data sources, traditional approaches often involve sharing data with third parties, raising concerns about bandwidth, privacy, and legal compliance. FL addresses these issues by enabling collaborative model training across distributed devices while keeping data local. This mechanism can help in building collaborative investment strategies which may be beneficial for INDIAN market

1.5 Research Purpose and Questions

My research aims to propose a working framework for prescribing effective investment based on investment behaviours. I propose the following framework for its working:

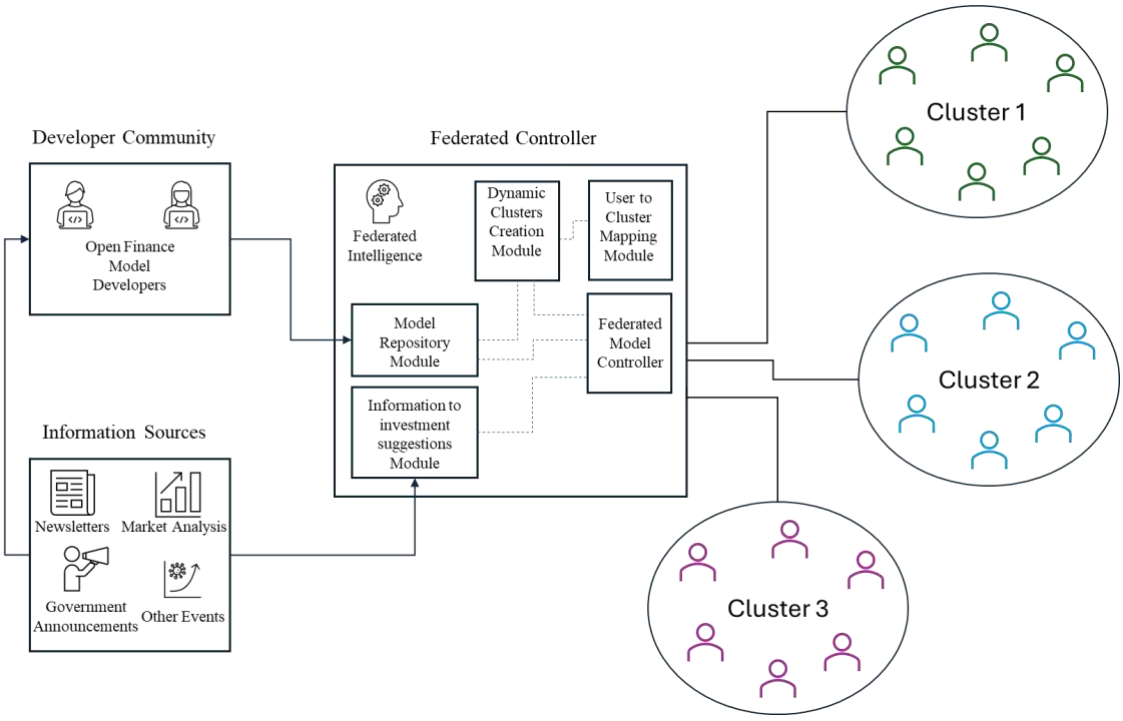

Figure 1: Proposed FML framework

In Figure 1, I demonstrate the federated platform architecture showcasing how clustered users can get benefits of information being processed and converted to investment suggestions. In this architecture users need not be an expert in making investment decisions, rather he/she can use global investment patterns to invest securely and confidently. In such scenarios, investments are mostly fruitful as they are backed up by a central governing body hence chances of fraud are not there. Information is local to end users and is not shared externally for inferencing. When a new user enrols on this platform, they are asked certain questions to evaluate priorities and investment patterns. Based on this information user is assigned a cluster, this cluster will have users of similar investment

appetite or behaviour. Users in a given cluster is given a federated model to prescribe behaviour-based investments. If the users like the suggestions provided, they provide positive feedback else they provide negative feedback. This feedback is used to update the federated model and adjust the weights and biases. This process is continuously followed until the model converges and provides the right investment to clustered users.

Specifically, the Following are the Research Questions I have tried to answer through my research:

1.5.1 What kind of bias in the investment information may impact an investor's decision-making?

1.5.2 Are the identified biases present in highly valued finfluencers over YouTube or online Blogs?

1.5.3 What are the common behavioural traits that exist in INDIAN investors?

1.5.4 How much is AI and ML impacting investment decision-making, i.e. How much of Digital Technology impact investment decision-making?

CHAPTER II:

REVIEW OF LITERATURE

2.1 Theoretical Framework

My research studies investment behaviours in INDIAN citizens and proposes unique behavioural clustering where any market change presented as news can be automatically filtered. This is important to remove unwanted news and bias in the news. The proposed framework is implemented using modern-day technology and advancements in FML.

("Do investors exhibit behavioral biases in investment decision making? A systematic review | Emerald Insight," n.d.) This paper explores biases prevalent in investment decision-making by reviewing research within behavioral finance. It traces the evolution of this field, examining its analytical foundations and the progression of research on individual, institutional, and financial advisor behavior. The study aims to provide an overview of behavioral patterns observed in investment decision-making across different market participants. This paper addresses a key gap in behavioral finance research by proposing solutions to reduce investor biases. While prior studies identified these biases, solutions were rarely explored. The authors discuss approaches suggested by (Nenkov et al., 2009) for improving financial information communication and (Cunningham, 2001) for integrating price formation into models to analyze investor behavior. Additionally, ("Reforming Investor Protection Regulation: The Impact of Cognitive Biases," n.d.) proposes a framework to mitigate framing, herding, and biases that contribute to stock market bubbles.

(Kalra Sahi and Pratap Arora, 2012) This research aims to segment Indian investors into distinct behavioral groups based on their biases, analyze their investment preferences and profiles, and ultimately provide valuable insights for financial institutions to better

cater to the unique needs and preferences of their clientele. An initial inventory of 97 potential biases was rigorously assessed for content validity and subjected to pilot testing and subsequent refinements. The final questionnaire, capturing eight key biases – Reliance on Experts, Overconfidence, Self-Control, Categorization Tendency, Budgeting Tendency, Adaptive Tendency, Socially Responsible Investing Bias, and Spouse Effect – was administered to 377 respondents. This study revealed four distinct investor segments: Novice Learners, Competent Confirmers, Cautious Anticipators, and Efficient Planners. This type of categorization demonstrates clear separation among people, which indicates groups formed for investment purposes can have more distinct characteristics compared to solo investors. Differences in risk acceptance together with levels of investment knowledge, expectations and strategies serve to highlight the different ways people approach investment. The variation between financial knowledge together with the limits on amount of funds availed for investment highlight the differences between persons in the same category.

The investment market of India is multifaceted and shaped due to several variables, including the state of the economy, political activities, and information dissemination. However, the actions of investors themselves are pertinent. (Bikas et al., 2013) describes how non-professional makes investment decisions and the impact of emotions and bounded rationality. This paper focuses on enabling investors with stronger predictive analytics of the market and the investment opportunities. This paper aims at enabling investors to better predict the market and investment opportunities. An interesting concept of the Adaptive Market Hypothesis (AMH) appeared in this paper, originally proposed by Tseng (Tseng, 2006), which is an improvement over EMH and is most applicable for high-frequency trades in the market. AMH is said to be superior to EMH because it utilizes more critical

factors necessary in making investment decisions. Conventional investment takes the assumption that:

1. An Investment Portfolio is based on expected return and risk-associated
2. Subject to risk-based asset pricing models such as the Capital Asset Pricing Model (CAPM). CAPM posits that the expected return of an asset is directly linked to its systematic risk or the risk that cannot be diversified away. This systematic risk is often measured by beta, which quantifies the asset's sensitivity to market movements
3. The fair value of an investment instrument whose payoff depends on the future state of some underlying asset
4. Modigliani-Miller's theorem (Villamil, 2008) states that in a perfect world, *capital structure* decisions would not impact a firm's value. However, in the real world, these decisions can have significant implications due to the presence of market imperfections

However, the above ideas do not answer the following and hence are missed in investor rationality:

1. Why does an investor invest?
2. How does an investor invest?
3. What are the rationales behind an investor's portfolio?
4. Why does the return on investment vary?

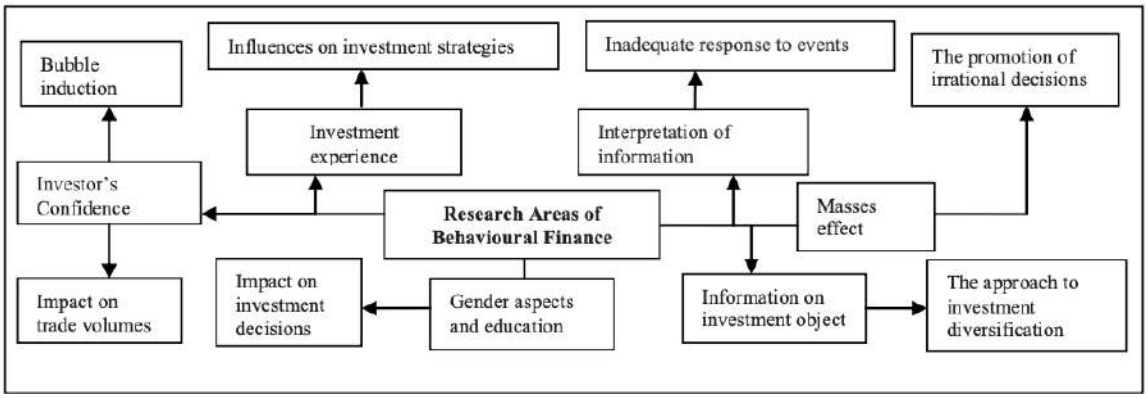

Figure 2: Research Areas of Behavioural Finance

(Graham and McGowan, 2003) Benjamin Graham, in his seminal work "The Intelligent Investor," emphasizes a crucial distinction between investing and speculating. Unlike speculators who prioritize short-term gains and market fluctuations, investors focus on long-term value creation. This necessitates a shift in perspective, prioritizing reasonable returns over chasing immediate profits.

(Subrahmanyam, 2008), following the work of (Tseng, 2006), argues that traditional finance, which assumes investors always act rationally, can be improved by incorporating insights from behavioural finance. Behavioural finance acknowledges that investors sometimes make decisions that don't align with pure logic. Subrahmanyam suggests that combining these perspectives can lead to more accurate predictions of not

just expected returns on investments, but also the events that can significantly impact those returns.

(Cheong et al., 2017) investigates a novel portfolio optimisation strategy. It utilises daily stock data from the Korean stock market to identify investment patterns among institutional and foreign investors. A clustering algorithm groups stocks based on these investment patterns. Then, a Genetic Algorithm (GA) is used to optimise portfolio weights, aiming to minimise risk while maximising returns. The study compares the performance of this approach with other portfolio management strategies using data from 2007 to 2014. However, if clustering can be done based on the behaviour of an investor instead of stocks and companies, the risk and loss could be reduced.

(Lakshmi et al., 2013) set out to study the unique behavioural patterns of India's long-term and short-term investors. This study surveyed 318 retail investors from India between January and May 2012. His study was grounded upon the assumptions of the Structural Equation Model (SEM) and focused on understanding the relationships existing between investment decision-making, some major behavioral biases -herding, overconfidence, loss aversion- and investor traits. The results obtained from SEM analysis revealed verifiable differences in behavior between long-term and short-term investors. The findings highlight the necessity of adapting the investment strategies and financial literacy interventions to the unique behavioral tendencies of investors within the Indian context.

(Sajeev et al., 2021) looks at how behavioral biases affect investment choices among investors of the Indian Gen Z group. The impact of financial literacy, risk attitude, herd behavior, and information search on investment choices is determined by applying Structural Equation Modeling (SEM). Empirical data for the study was collected from 144 individuals from Gen Z residing in Maharashtra, India between January 2021 and May

2021. This evaluation framework utilized confirmatory factor analysis to validate the measurement scales and control path analysis to confirm the hypothesized link between behavioral biases and investment decisions. The findings of the study reveal a positive relation between the behavioral biases and the investment activities of Indian Gen Z investors that call for proper financial education and awareness intervention for this group.

(Raut et al., 2018) in their study gathered data on financial investments from the Indian states of Jharkhand, Bihar, Orissa, and West Bengal. A total of 396 investors were included based on the following demographic characteristics:

Table 5: Demographic Profile of Respondents (n=396)

Variable	Category	Frequency	Percentage
Gender	Male	289	73
	Female	87	27
Age	< 20 Years	0	0
	20 – 30 Years	130	33
	31 – 40 Years	148	37
	41 – 50 Years	82	21
	> 50 Years	36	9
Marital Status	Married	278	72
	Unmarried	118	28
Education	< High School	19	5
	High School	13	3
	Diploma	9	2
	Bachelor's Degree	197	50
	Post Graduate	158	40

Annual Income	< 200000	78	20
	200000–300000	23	6
	300000–500000	158	40
	>500000	137	34

The above data is used with a statistical method called *Structural Equation Modeling (SEM)* for analysis. SEM is helpful because it allows us to test the entire research model and also account for any errors in how we measure things. From the results derived using *python semopy* package, Raut concluded that behavioural biases are inseparable from human beings' decision-making. As the financial market can appear to be the prominent segment where investors lose their hard-earned money due to socio-psychological factors, they need to understand these biases.

I have used semopy and SEM to model the collected data and the results given in this paper to form behavioural clusters. With the derived results, I propose to automate and provide a platform which helps investors understand the market well and secure their investment decisions without sharing their data over the Internet.

2.2 Theory of Reasoned Action

(Shanmugam et al., 2022) investigates the interplay between information behaviour, financial knowledge, and sustainable investment decisions among Indian investors. Data collected from 301 investors in southern India revealed significant positive associations between information access and subjective financial knowledge and between these factors and information behaviour. Furthermore, the study found a positive relationship between risk propensity and sustainable investments, with risk propensity mediating the influence of information behaviour on sustainable investment choices. These findings underscore the crucial role of accessible and reliable financial information and robust financial literacy in driving sustainable investment decisions among Indian investors."

Active portfolio management of investments is becoming more efficient with a new approach proposed by (Cheong et al., 2017) which allows investors to take advantage of useful information at hand. Investors are classified into various groups with the help of cluster analysis which guides the creation of an appropriate investment strategy for each group. Also, within each group, genetic algorithms can be applied to decide the best stock allocation. This investing technique allows for portfolio rebalancing to maximize profits. The multi-stage optimization technique used here has proved to repeatedly beat the existing stock investment strategies in the Korean stock market, greatly aiding investors in customizing their portfolio to fit their needs..

Investments can also be processed from a behavioral perspective along with the others, for instance, EMH or AMH. One strategy I propose is to use clustering to categorize investors and then be able to make relevant investment suggestions.

In my research, I demonstrate how investors can be grouped (clustered) based on their behaviours and appropriate investment suggestions can be provided. For providing

efficient suggestions on plausible investments, an efficient mechanism is envisioned, which processes the fast-passed market data in real-time and derives meaning from it.

Many investors struggle with information overload and the potential for misinterpretation, leading to suboptimal investment decisions. To address these challenges, technology-driven solutions are crucial. By leveraging data analytics and artificial intelligence, investors can benefit from personalized information filtering and tailored investment recommendations. These technologies can help mitigate the impact of biases and emotional impulses, enabling more informed and objective investment choices.

2.3 Human Society Theory

INDIAN culture is deeply rooted in collectivism, emphasising the importance of family, community, and social harmony. Indians prioritise long-term family goals over short-term financial gains. In Indian society, preference is given to stability, and it is recommended to avoid uncertainties. As kinship and family networks are strong, there are many family influencers that assert any investment.

Based on research conducted on the National Stock Exchange of India ("PR_cc_08082024.pdf," n.d.), the mean age of people with investments is now 32 years and this number will only grow as we approach March 2024. This clearly shows the maturity of investors, Indians tend to start investing around their 30s ("Investors under 30 years dominate Indian stock market, participation from 60 plus age group dips: NSE," n.d.). This shift indicates that the younger population is becoming more inclined towards the stock market as older generations are starting to participate less and less. It is apparent that the youth of India is educated enough to make investment decisions but the real question is whether they are affected by cognitive biases.

Finfluencers becomes a portmanteau of "financial influencers" and they are now an emerging power in the Indian stock market. This helps elevate the influencers role and enforces guidelines for them. Because the youth lacks the understanding of finance, they are seeking the help of finfluencers in making investment decisions. The authors portray an underlying warning to the audience which is why using social media as their sole decision-making tool could be dangerous ("As Finfluencers Grow, Can Sebi's Regulations Snap Investors Out Of Their Fantasy World?," n.d.).

According to a study by (Kumar, 2024) finfluencers, which range from stock experts to crypto gurus, have significant influence over social media users who are traditional investors (retail investors) with inadequate investment knowledge. This study

seeks to measure the independent impacts of two of these influences: the finfluencer's credibility (trustworthiness, goodwill, expertise) and the social media user's level of understanding of finances or financial literacy. Breaking these factors apart is difficult, however. An online survey of residents of Chennai has found that finfluencer credibility indeed enhances investment decisions. In addition, both high and low financial literacy levels influence investments. This will aid finfluencers, retail investors, and Indian fintech companies. This paper shows that it is important for the people to verify the information that they are going to base decisions from, especially information from social media because this may contain false information. It also shows how the information in social media is always easier to gain, but there is a need to evaluate the information critically. The government must consider AI-integrated systems to monitor social media information and prevent the spread of misinformation. There is a need to further investigate the social media's effects, both positive and negative, on different people. Families and schools ought to enable youngsters to become responsible and discerning users of social media. The adoption of open-source, AI-driven fact-checking technologies can pave the way for better individual assessment of the quality of information disseminated on social media.

In my research, I propose a framework which tests the provided suggestions against the legal news issued by the government of India and transforms this information into proper investment suggestions that are easy to render by anyone. Also, the suggestions are custom-built based on the investor's behaviour.

2.4 Summary

In my research, I would like to show the impact of bias or misinformation leading to lossy investment decisions, However, as EMH clearly states market moves based on the information spread and the movement can result in profits for some while a loss for others. The market always remains in equilibrium if no new information is shared.

Such an equilibrium of an efficient market is impossible in modern Indian society. In my research, I study the impact of investors' behaviour and their decision-making under various market conditions. This observation then leads to the clustering of various behavioural portfolios without sharing their local and sensitive data with the external world.

The proposed system then gathers the market news and translates it to appropriate investment opportunities for various investor clusters. This research finally reveals a working federated model that sits on investors' devices and helps him/her make the right financial decisions based on respective investment behaviours.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

Technological advancement has gone at a breakneck speed within which people have become ‘tech-savvy’ giving rise to an information overload which can prove to be detrimental in the decision making of investors. As the markets get more complex in their dynamics, historic data based traditional investment strategies will fail without an augment of advanced techniques such as fundamental analysis. Harnessing the advancement in the artificial intelligence field, investment federacies can easily bolster the identification of emerging trends, camouflaged opportunities, as well as concealed risks. The focus of this research will be on the integration of cutting edge technologies into the decision making of federated investment frameworks to foster improved outcomes.

My thesis discusses the relationship between the Efficient Market Hypothesis (EMH) against Behavioural Investments and strategies to form a federated investment architecture that deals with information inefficiencies. EMH states that information is always available and hence investments markets are efficient, which faces challengers due to markets existing in the real world that suffer from prolonged information asymmetries. Such delays lead to poor investment choices being made as well increases the risks being taken. The deployment of modern technologies such as smart devices alongside the investment analytics of one’s behaviour enables the pooling and sharing of insights and resources which augments decision making..

3.2 Operationalization of Theoretical Constructs

Conducting qualitative analysis allows identification of patterns which makes it easier to group investors according to their investment patterns. These patterns are used for grouping the investors according to their investment patterns. With the help of Chi-square tests it is easy to examine the strength of relationships between many categorical variables since most of the data is sourced from searching for answer. (Franke et al., 2012) which examines the analysis of the chi-square test allows to correlate the variables in a categorical manner. The examination of correlation helps me to identify the mistakes or discrepancies in the obtained data and therefore make rationals decisions when it comes to clustering the investors.

The very first step is to find the correlation among various variables. Structural equation modeling (SEM) is a sophisticated method for examining the structure of relationships among factors affecting investment behaviors because they are many. Within SEM research, I can study the intricate relationships among investor behavioral biases including overconfidence, herding, loss aversion, information gaps such as low financial literacy, inadequate information, and finally, the investment decision itself.

By mapping out the causal relationships among these structures semi-structured. These relate to the constructs that cannot be perceived but can only be evaluated indirectly and include survey response, investment patterns, and financial performance. This means that SEM gives an overall strategy for identifying the most important aspects that drive investment behaviour and helps explain to SMEs how these interact in determining investment results. Such understanding will aid the formulation of specific behavioural modification programs and support systems aimed at reducing bias, increasing financial literacy, and enabling SMEs to make better investment decisions.

SEM can indeed be used to analyze the impact that the physiological signals, or hints, given by finfluencers may have on the investor's motivation and ill-directed investment decisions, if any.

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Latent Constructs:

Influencer Influence: This latent construct may include credibility, charisma, emotional appeal, and persuasive speech given by finfluencers.

Investor Motivation: This can include FOMO, herd mentality, lust for quick profits, and social status.

Investment Decisions: This may include risk tolerance, investment options (high risk assets versus low risk assets), and investment results.

Physiological Responses: Such other dimensions of the latent construct could include measurable ones such as heart rate variability, skin conductance, and even facial expressions during or after watching a finfluencer's content.

Observed Variables:

Finfluencer Influence: Perceiving such input can be gauged by social media activity such as those arising from shares, comments, and likes as well as looking at the image sentiment on finfluencer posts/reels.

Investor Motivation: Observed variables could include survey responses on investment goals, risk tolerance, and perceived financial knowledge.

Investment Decisions: Observed variables could include investment portfolios, trading activity, and financial performance data.

Physiological Responses: Observed variables could include data from wearable devices (e.g., smartwatches) or facial expression analysis software.

SEM Analysis:

SEM can model the complex relationships between these latent constructs. For example, it can test hypotheses like:

- Does the perceived credibility of a finfluencer directly influence investor motivation?
- Does the use of emotional appeals by finfluencers significantly impact investor FOMO and subsequent investment decisions?

SEM can also model the performance of any investment tool as a good or bad investment, by analysing:

- Key drivers of a company's financial performance. For example, it can model the relationships between factors like research and development (R&D) expenditure, marketing effectiveness, competitive advantage, and ultimately, revenue growth and profitability
- Investment tools like mutual funds or ETFs. SEM can analyse the impact of factors such as the investment strategy, fund manager expertise, market conditions, and risk exposure on the fund's overall performance
- Relationship between risk factors (e.g., market volatility, interest rates, competition) and investment returns

SEM is an integration of different multivariate techniques into one model-fitting framework. It integrates:

1. Measurement Theory
2. Factor (Latent Variable) analysis
3. Path Analysis
4. Regression
5. Simultaneous Equations

In my research, I plan to use SEM for modelling investor behaviour, processing and filtering the news spread through online articles, and by finfluencers. This can be thought of as modelling causal system for helping investors react appropriately to news and events happening in the investment market.

However, for deploying SEM-based models, I will use the FML framework to showcase Adaptive Investor Clustering (AIC). In the end, FML will also prove to be useful in preserving investment choices securely on investor's devices.

3.3 Research Purpose and Questions

Behavioural Investment is a field that seeks to understand how psychological factors influence decision-making. It's based on the premise that investors are not always rational and can be influenced by emotions, biases, and social factors. ("What Is Behavioral Finance?," n.d.) claims that people often make financial decisions based on emotions rather than rationality. (Ige and Adebayo, 2024) suggests that individual investors need to acknowledge and understand the psychological factors influencing their investment decisions and how to take note of them to make better decisions. It also suggests financial advisors integrate behavioural insights into investment strategies.

The purpose of this research is to study the impact of considering behavioural insights into investment decisions. This research also provides a federated investment framework for investment, hence proposing a secure and safe implementation of the proposed methodology.

The questions that I have tried to answer in my research are the following:

3.3.1 What kind of bias exists in the investment information that may impact an investor's decision-making?

By identifying and acknowledging biases, in publicly available information, an investor can get educated and make informative decisions. Such analysis provides a robust system where the chances of being misled are very low.

3.3.2 Are the identified biases present in highly viewed finfluencers over YouTube?

Finfluencers are modern-age educators who govern the spread of knowledge about a particular investment tool or asset. However, in many

instances, it is found that they tend to be biased and lurk viewers in uneducated investments.

3.3.3 What are the common behavioural traits that exist in INDIAN investors?

Studying the behavioural traits of Indian investors is crucial for my research, as it helps in suggesting an investment landscape that helps investors to be more informed and efficient

3.3.4 How much is AI and ML impacting investment decision-making, i.e. How much of Digital Technology impact investment decision-making?

In assessing this impact, it is clear that AI/ML models capable of handling enormous datasets in investment, pattern recognition, and making previously impossible predictions will work. My research aids in estimating the potential advantages (better risk management, portfolio diversification, and investment returns) and obstacles (algorithmic bias, ethical issues, and even market manipulation) that could accompany this technological change. These insights are invaluable in grappling with the issues surrounding the changing dynamics of the financial world, and facilitating responsible, just, and equitable access to investment opportunities..

3.3.5 What challenges and problems exist with current digital technology in investment decision-making?

Researching limitations and issues of concern in the context of investment decision-making with modern digital technology is important to contain risk and enhance the experience of investors. These technologies may offer convenience and access to information, but the same technologies can also be biased, allow emotional decision making, and cause increased vulnerability to fraud. These issues are critical for the development of

adequate measures of protection and the regulation of digital investments in an ethical manner..

3.3.6 How FML will help create a Strong Foundation for INDIAN Federated Investments?

With respect to the Indian Federated Investments, it is vital to focus and study FML since it provides an opportunity to train models in a collaborative manner while protecting the sensitive information which is paramount in the finance industry. Utilizing FML, financial institutions can integrate data from different types of businesses (such as banks and insurance companies) to refine investment models without disclosing critical client data. This encourages innovation, improves risk management, and results in a more wholesome and safe financial environment in INDIA..

3.4 Research Design

Finfluencers Analysis:

Finfluencers' content analysis is crucial and required for gaining valuable insights that contribute to influencing investors towards a specific asset or company. Following are the common names of 15 finfluencers channels on YouTube as of September 2024:

Table 6: List of finfluencers channels used for this research

Finfluencer Name	YouTube Channel	Description	Approximate Subscribers
Pranjal Kamra	Pranjal Kamra	In-depth analysis of stocks, mutual funds, and personal finance	6.7M
Ankur Warikoo	Ankur Warikoo	Wide range of financial advice, including investing, entrepreneurship, and personal finance	5.28M
FinnovationZ by Prasad	FinnovationZ	Simplifies complex financial concepts and provides practical advice	2.54M
CA Rachana Ranade	CA Rachana Ranade	Expert insights on personal finance, taxes, and investments	5.1M
Groww	Groww	Educational content on investing, mutual funds, and stock market basics	2.36M
Investor's Clinic	Investor's Clinic	Detailed analysis of stocks, mutual funds, and IPOs	2M+

Savvy Investor	Savvy Investor	Practical advice on personal finance, investing, and retirement planning	1M+
StockPro	StockPro	Technical analysis and trading strategies for the stock market	3M+
Finance with Vineet	Finance with Vineet	Mix of personal finance, investing, and stock market analysis	1M+
Nikhil Kamath	Nikhil Kamath	Insights on trading, investing, and entrepreneurship	2M+
Stock Market India	Stock Market India	Technical analysis and trading strategies for the Indian stock market	2M+
Moneycontrol	Moneycontrol	News, analysis, and insights on the Indian financial markets	2M+
CA Rahul Malhod	CA Rahul Malhod	Business Coach, provides financial advice and insights	1M+
Anurag Aggarwal	Anurag Aggarwal	Business Coach, provides financial advice and insights	1M+
Geojit Spotlight	Geojit	Latest news, insights, and analysis on the economy, markets and investment avenues.	102K

For the above list of YouTube Channels following are the behavioural traits to be observed:

Table 7: Behavioural Traits in finfluencers market analysis

Behavioural Trait	Description	Mathematical Constructs
Information Asymmetry	Finfluencers may possess specialized knowledge or insights that viewers may not have access to, potentially creating an imbalance in information.	Certification SCore (CSC) $CSC = \begin{cases} 0: For\ No\ Credentials \\ 1: for\ Basic\ Cerdentials \\ 2: For\ Advanced\ Certications \end{cases}$ Information Asymmetry Score (IAS) $IAS = \frac{1}{(1 + CSC)}$
Perception of Expertise	Titles like "CA" or "Financial Advisor" can enhance perceived expertise and influence viewer trust, even if it doesn't always reflect actual qualifications.	
Social Proof	Large followings and high subscriber counts can create a sense of social validation, leading viewers to perceive the finfluencer's advice as widely accepted and trustworthy.	Subscriber CounT (SCT) Subscriber Count Score (SCS) $SCS = log_{10}(SCT)$ (Logarithmic scale to account for exponential growth) Engagement RaTe (ERT) $ERT = \frac{(Likes + Comment)}{Total\ Views}$ Social Proof Score (SPS)

		$SPS = \frac{(SCS * ERT)}{100}$
Emotional Appeals	Use of storytelling, personal anecdotes, and emotional language can evoke strong emotions in viewers, potentially influencing investment decisions based on feelings rather than logic.	Emotional Appeal Score (EAS) Positive Word Count (PWC) Negative Word Count (NWC) Word CounT (WCT) $EAS = \frac{(PWC - NWC)}{WCT}$
Fear of Missing Out (FOMO)	Highlighting success stories and emphasizing potential for high returns can trigger FOMO, pushing viewers to make impulsive investment decisions.	FOMO Score (FOS) $FOS = \frac{Frequency\ Of\ FOMO\ keys}{Total\ Number\ of\ Keys}$
Availability Bias	Focus on recent market trends or news events can lead viewers to overestimate their importance and make investment decisions based on short-term fluctuations.	Count of Investment Opportunity (CIO)

The results from analysing the above traits will provide the case for their impact on the INDIAN population. To understand how much a finfluencer has manipulative or misleading behaviour, I am using the weighted average method, hence Finfluencer Manipulative Capability Score (FMCS) can be calculated as follows:

$$FMCS = (IAS * w1) + (SPS * w2) + (EAS * w3) + (FOS * w4) + (CIO * w5) + (Experience * w6)$$

Where weights are defined as:

$w1 = Weight\ for\ IAS = 0.1$

$w2 = Weight\ for\ SPS = 0.25$

$w3 = Weight\ for\ EAS = 0.15$

$w4 = Weight\ for\ FOS = 0.3$

$w5 = Weight\ for\ CIO = 0.2$

$w6 = Weight\ for\ Finfluencer\ Experience = 0.1$

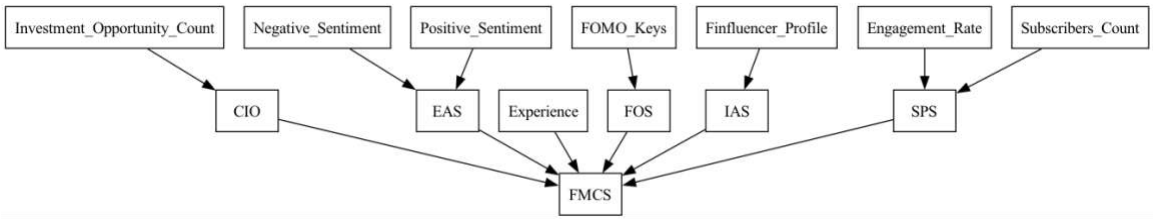


Figure 3: SEM for FMCS

Impact of credibility of finfluencer. The hypothesis is that years of experience and qualifications play a vital role in establishing trust among viewers:

$H1_0 =$

$More\ experience\ and\ less\ information\ asymmetry\ results\ in\ better\ credibility$

$H1_1$ = Experience and Information asymmetry have nothing to do with credibility

$w7 = Weight\ for\ Years\ Of\ Experience = 0.6$

$w8 = Weight\ for\ Information\ Assymetry = 0.4$

$$Normalised\ Experience = \frac{Finfluencer\ Years\ Of\ Experience}{Maximum\ Years\ Of\ Experience\ in\ Sample\ Set}$$

$$Cred\ Score = (Normalised\ Experience * w7) + (IAS * w8)$$

Impact of Finfluencer Media Dominance. The hypothesis is that higher social proof and emotional appeal to viewers impact investors' beliefs more.

$H2_0 =$

$Higher\ social\ proof\ and\ emotional\ appeal\ score\ results\ in\ investor\ attention$

$H2_1 =$

$Social\ proof\ and\ emotional\ appeal\ results\ has\ no\ impact\ on\ investor\ attention$

$w9 = Weight\ of\ social\ proof\ score$

$w10 = Weight\ of\ social\ proof\ score$

$$Finfluencer\ Media\ Dominance = (SPS * w9) + (EAS * w10)$$

Impact of Content Posted. The hypothesis is that better investment opportunities or FOMO creation results in higher viewer attention and belief.

$H3_0 =$

$Higher\ investment\ opportunities\ and\ FOMO\ created\ results\ in\ investor\ attention$

$H3_1 =$

$Investment\ opportunities\ and\ FOMO\ created\ has\ no\ impact\ on\ investor\ attention$

$w11 = Weight\ of\ FOMO\ score = 0.5$

$w12 = Weight\ of\ investment\ opportunities\ score = 0.5$

$$Viewer\ Attention\ Score\ = (FOS * w11) + (CIO * w12)$$

Investors Analysis:

To understand the investment behaviour of INDIANS, a survey-based approach was used, and the following questions were curated and answered by 50 investors. The questions were:

1. Are you an active investor? ["Yes", "No"]
2. Which age bracket you fall in? ["<20", "20-30", "31-50", ">50"]
3. Marital Status? ["Married", "Unmarried"]
4. Years spent in investment? ["<1 years", "1-3 years", "4-6 years", "7-10 years", ">10 years"]
5. Highest level of education received? ["< High School", "High School", "Diploma", "Bachelor Degree", "Post Graduate"]

Impact of Age on Investment. Does age have any impact on the longevity of investment that a person makes?

$$H4_0 = Older\ investors\ have\ larger\ investment\ horizons$$

$$H4_1 = Young\ investors\ have\ larger\ investment\ horizons$$

Impact of Gender on Investment. Do males have higher investment horizons than females?

$$H6_0 = Males\ remain\ invested\ for\ longer\ time$$

$$H6_1 = Gender\ has\ no\ relation\ with\ investment\ horizons$$

Financial News Gathering:

Yahoo Finance is a valuable resource for financial and investment research. It provides important insights due to the following:

1. **Comprehensive Data:** It offers a wide range of financial data, including historical stock prices, financial statements, market news, and analyst ratings. This breadth of information allows for in-depth analysis of companies, industries, and market trends.
2. **Free Access:** The majority of Yahoo Finance's core features, including real-time quotes, historical data, and financial news, are available for free, making it accessible to a wide audience.
3. **API Availability:** The Yahoo Finance API allows developers to integrate financial data into their own applications and perform automated tasks, such as portfolio tracking, backtesting trading strategies, and developing custom financial analysis tools.

Investors in INDIA have access to various investment options. From Yahoo Finance APIs, 1216 individual companies can be fetched with their updated news data. This news headline can be used to evaluate risks and decide whether to buy or sell these assets based on an investor's classification.

It is important to analyse how news is analysed. For my research following parameters are evaluated for any news content:

1. **Confirmation Bias:** If someone already holds a positive view of the Indian market, this statement might confirm their existing beliefs, leading them to overestimate the market's growth potential or overlook potential risks.

2. **Availability Bias:** The focus on growth opportunities may make the market seem more attractive than it is or vice versa. This can lead to an overemphasis on the positive aspects and a neglect of potential challenges or risks.
3. **Oversimplification:** Latest market news may not sufficiently describe the subtleties of regional differences, competition, operational dynamics, regulation and other factors that are known to influence the development of the market and the prospects for it profitability.
4. **Framing Bias:** Using specific terms like "opportunities, Booming market, Thriving industry, Explosive growth, Revolutionizing the industry, Leading the charge" can create a positive frame around the market, potentially leading to an overly optimistic outlook.

The above biases are detected by analysing the phrases mentioned in the news text. These biases in news impact a biased investor in many ways. Like:

1. **Confirmation Bias:** Investors may selectively seek out and interpret news that confirms their existing investment biases, such as overconfidence in their own judgment or a tendency to avoid information that contradicts their investment positions.
2. **Availability Bias:** Investors may overweigh recent or easily recalled information (e.g., a recent market crash) when making investment decisions, even if it's not statistically relevant as availability bias ensures hyped information rather than surfacing true facts.
3. **Framing Bias:** Investors may be more sensitive to losses ("loss aversion") and frame their investment decisions based on avoiding losses rather than maximising gains. Framing bias works by aggravating investors' bias of fear or successful affirmation.

4. **Oversimplification Bias:** Investors may oversimplify complex financial concepts, leading to unrealistic expectations and poor decision-making.

Investors Clustering:

Clustering investors based on their behaviour traits. In this research I have employed k-means clustering, an unsupervised machine learning algorithm, to segment investors based on their investment behaviour. By analyzing key behavioural attributes such as risk tolerance, investment horizon, preferred asset classes (stocks, bonds, real estate, etc.), trading frequency, and response to market volatility, k-means clustering effectively groups investors with similar investment profiles. This segmentation enables a deeper understanding of investor heterogeneity and allows for the development of more personalized investment strategies and financial advice tailored to the unique characteristics and preferences of each investor cluster.

Clustering is dependent on the investor's portfolio. An Ideal investor portfolio looks like the following:

Table 8: Investor Portfolio Structure

Field	Type	Description	Info
Investor Id	Number	Unique Id of investors	Synthetic
Asset Name	List	Name of the stocks randomly picked	Real
Quantity	Number	Quantity of assets purchased	Synthetic
Purchase Price	Float	Purchase price of given asset	Real
Purchase date	Date	Random date between given duration	Synthetic
Current Price	Float	Current market price of given asset	Real
Market Value	Float	$Quantity * Current\ Price$	Derived
Cost Basis	Float	$Quantity * Purchase\ Price$	Derived
Unrealized Gains/Losses	Float	$Market\ Value - Cost\ Basis$	Derived

Beta	Float	Determine the volatility of a stock	Real
Investment Horizon	Number	Years investor plan to invest in given asset. It is correctly represented by beta distribution as average investment horizon is found to be around 3 to 5 years.	Synthetic
Expected Return	Percentage	For each asset the accepted return percentage	Synthetic
Risk Free Rate	Percentage	What is the risk appetite expressed in interval for every asset. It could be same across portfolio or individual for each asset	Synthetic
Standard Deviation	Percentage	Acceptable deviation in returns	Synthetic
Sharpe ratio	Float	$\frac{(Expected\ Return - Risk\ Free\ Rate)}{Standard\ Deviation}$	Derived

For this research, the dynamic clustering of the portfolio depends on what an investor discloses. Investor clustering data can be synthetic to test the clustering phenomena. The benefits of adding synthetic data are:

1. **Removing Recall Bias:** Investment quantity and quality require strong recall, especially for those assets that have been done over extended periods
2. **Removing Social Desirability Bias:** Individuals may be inclined to report investment behaviours that they perceive as socially desirable or align with societal expectations, even if they don't accurately reflect their actual behaviour. For example, they may underreport risky investments or overreport successful ones
3. **Removing Lack of Objectivity:** Self-reported data lacks the objectivity of verifiable data sources like brokerage records or financial statements. This makes it difficult to assess the accuracy and reliability of the information.
4. **Removing Lack of Data:** Using Synthetic portfolios I can easily generate sufficient data sets to test theories under different scenarios.

Using this investor profile, I created 2000 investor profiles investing in 1216 companies listed using Yahoo Finance discussed above. Using these profiles I cluster them using a k-means clustering algorithm. (Gülagiz and Sahin, 2017) helps in identifying the right clustering method.

Table 9: Comparing clustering algorithms

Clustering Algorithm	Strengths	Weaknesses
K-Means	Simple and efficient	Sensitive to outliers, requires specifying k, assumes spherical clusters
K-Medoids	More robust to outliers than k-means	Can be computationally more expensive
Hierarchical	No need to specify k, provides a dendrogram	Can be computationally expensive, sensitive to distance metric
DBSCAN	Discovers clusters of arbitrary shape, good for identifying outliers	Sensitive to parameter selection, may not work well with varying densities
Gaussian Mixture Models (GMM)	Models complex cluster shapes, provides probabilistic assignments	Can be computationally expensive, sensitive to initialization

Post Clustering Analysis:

Using FML, a base model is published for each cluster which will behave differently in each cluster for recommending investments. Each model will have different config settings for recommendations. Models will work as follows:

a. **Model Input:** Market news and events serve as the primary input for the model.
b. **Model Processing:** The model utilises the published model to selectively filter incoming news and events, focusing on those deemed relevant and potentially impactful. After processing and interpreting the news, the model identifies and presents potential investment opportunities to the investors.
c. **Model Output:** The mathematical model rigorously evaluates the news based on a predefined set of criteria. Only news that meets the model's qualification criteria is presented to investors as a potential investment opportunity.
d. **Model KPI:** The success of this model is ultimately measured by the acceptance rate of the recommended investments by investors.

This mechanism allows investors to move across clusters based on the KPI and newly revealed information. This is the cornerstone of this research where behaviour investments are considered to establish adaptive market efficiency.

3.5 Population and Sample

Finfluencer Analysis:

Finfluencers are mostly active on social media platforms like YouTube, Instagram, Facebook etc. With the modern revolution of Generative AI, there will be many AI platforms where Finfluencers can influence people more effectively. As the population of finfluencers on YouTube is indeterministic and ever-growing it is important to cover the ones with maximum viewership. For the finfluencers mentioned in Table 6, I have analyzed **20 hours** of meaningful video data to highlight influential traits like IAS, SPS, EAS, FOS, CIO and relevant Experience. This data has presently **9458177.00 views, 234641 Likes** and **16769 comments** to indicate maximum engagement.

Investors Analysis:

According to ("The rise and rise of retail investors," n.d.) around **10 Crore**, there are direct investors involving the HNI segment and retail or individual investors. This number is also ever-growing based on SEBI's promotions and advertisements.

To calculate the desired sample size I use the following calculations:

$$n = \frac{(Z^2 * p * (1-p))}{E^2}$$

$Z: Z - Score. Indicates\ the\ confidence\ level. For\ 95\%\ confidence, I\ set\ it\ to\ 1.96$

$p: Estimated\ proportion\ of\ the\ population\ that\ possesses\ the\ characteristic,$

$I\ set\ it\ to\ 0.5\ to\ maximize\ the\ sample\ size$

$E: Desired\ margin\ of\ error, I\ set\ it\ to\ 0.05$

Putting these values to calculate sample size n gives:

$$n = \frac{(1.96^2 * 0.5 * (1-0.5))}{0.05^2} = 384$$

Hence, a sample size of 384 investor population should be good for understanding some behavioural traits.

Investors Clustering:

Based on the investor analysis, I have created synthetic data for 2000 investors with data points mentioned in Table 8 “Investor Portfolio structure”. The same data will be used to test the hypothesis testing. For these 2000 investors, the following are the rationale for data generation.

Table 10: Investor Profile Generation

Field	Description	Rational For Generation
Investor Id	Unique Id of investors	Incremental Id to identify investor
Asset Name	Name of the stocks randomly picked	Current Holdings as list randomly generated between 1 and 500
Quantity	Quantity of assets purchased	For each asset random quantity between 10 and 100
Purchase Price	Purchase price of given asset	For the randomly selected investment asset the price is known and being imputed with a random fluctuation using normal distribution
Purchase date	Random date between given duration	Random purchase date related to purchase price
Current Price	Current market price of given asset	Today's price for given asset
Market Value	Current aggregated market value	Quantity * Current Price
Cost Basis	Current aggregated Cost of purchase	Quantity * Purchase Price
Unrealized Gains/Losses	Current aggregated gains or losses	Market Value - Cost Basis
Beta	Determine the volatility of a stock	Systematic Risk and Volatility relative to overall market
Investment Horizon	Years investor plan to invest in given asset. It is correctly represented by beta distribution as average investment horizon is found to be around 3 to 5 years.	Using Beta Distributions to generate values between 1 and 11 years
Expected Return	For each asset the expected return percentage	A Uniform Random variable representing expected returns

Risk Free Rate	What is the risk appetite expressed in interval for every asset. It could be same across portfolio or individual for each asset	Safe value 0.01
Standard Deviation	Acceptable deviation in returns	Standard Deviation on returns calculated as uniform random variable between 0.1 and 0.5
Sharpe ratio	Provides a measure of an investment's risk-adjusted return.	(Average Expected Return percent - Risk-Free Rate) / Standard Deviation

These 2000 investors will be clustered using hierarchical clustering.

3.6 Participant Selection

Finfluencer Analysis:

In Table 6 I have selected effective finfluencers because they exhibit commonalities such as :

1. **Focus on INDIAN Market:** All channels primarily cater to the Indian investment market, addressing the concerns and interests of Indian investors.
2. **Diverse Approaches:** The channels represent a diverse range of approaches to financial education. Some focus on technical analysis (StockPro), some on fundamental analysis (Investor's Clinic), while others emphasize personal finance and behavioural finance (Ankur Warikoo, Pranjal Kamra).
3. **Established Presence:** Most channels have a significant following and have established themselves as credible sources of financial information within the Indian investment community.
4. **A mix of Individual and Institutional Presence:** The list includes individual finfluencers (Pranjal Kamra, CA Rachana Ranade, Anurag Aggarwal) as well as channels representing financial institutions (Groww, Geojit Spotlight, Moneycontrol).

This diversity in approach, coupled with their established presence and focus on the Indian market, makes this selection of finfluencers suitable for my research.

Investors Analysis:

Selection of investors includes careful selection of demographies like:

1. **Individual Investors:** People who invest their own money in stocks, bonds, mutual funds, or other financial instruments.

2. **Professional Investors:** Financial advisors, fund managers, and other professionals who make investment decisions for themselves or on behalf of others.
3. **Corporate Executives:** Business leaders who make financial decisions for their companies, such as investments, mergers, and acquisitions.
4. **Policymakers:** Government officials involved in setting financial regulations and policies.
5. **Students:** Individuals studying finance or related fields who can provide insights into their understanding of financial concepts and decision-making.

3.7 Instrumentation

The objective of my research is to propose a secure framework that allows investors to get appropriate recommendations on investments based on their behavioural traits. With the proposed framework investors can get relevant recommendations which they can relate to. The proposed framework helps investors maintain the privacy of their investment data as it's not shared on any cloud or external storage. The objective is to load prescriptive models on investors' devices and continuously improve to provide better investment opportunities.

In this research, I have studied advice given by finfluencers along with the financial news coming out through digital and paper media and its impact on the Indian investor population.

It is pretty evident that for any investor willing to invest by themselves knowledge about the market is necessary. I do not cover trading which is primarily for short durations, rather focus on promoting long-term investments by providing suitable opportunities which otherwise would have not been possible.

The crucial component of my research is first to identify the pattern of investment in long-term investors and not a day trader. For this I conducted a paid survey of 50 new investors and identified what kind of population invests and in what type of investments. This will help me define the type of population sample I need to conclude my research.

Once I have my population sample defined I will give them some questions to identify their investment behaviour. These questions are defined in the Investor Clustering section above. Based on the answers the sample investors are grouped as a cluster. These clusters are then given AI Model to take inputs from digital feeds and other information channel and filter out potential investment opportunities for each cluster.

As behaviour is not fixed for an investor they may get moved to different clusters based on their actual investment patterns.

My research is mostly Qualitative, and in some places where I have to do quantitative analysis as well to understand returns and forecast good investments.

3.8 Data Collection Procedures

Getting investment patterns from investors in India is difficult, hence I used paid surveys to collect data. I collected data from different geographies aiming to identify who are the prime investors. In this survey, I asked close and open-ended questions. They are:

1. How many years have you spent in investment? – Using it to gauge an individual's experience and expertise in the field of investing
2. Preferred type of investment? - By understanding the respondent's preferred investment type, I can gain valuable insights into their financial knowledge, investment goals, and risk tolerance
3. Motivation for investment? - Understanding why someone invests helps develop investment strategies to specific needs
4. What are the improvements in the investment framework required? – How can Government evaluate the effectiveness of their investment policies and identify areas where improvements could be made to stimulate economic growth and development? This question also helps me understand investors' trust in existing policies
5. How long do you plan to stay invested? – This questions helps my research to create investor personas and eliminate behaviours of short term investors.

The above questionnaire aims to understand the population sample. For this population sample, I will conclude the attributes and behaviours of investors.

3.9 Data Analysis

Finfluencer Analysis:

Impact of credibility of finfluencer. The hypothesis is that years of experience and qualifications play a vital role in establishing trust among viewers:

$H1_0 =$

More experience and less information asymmetry results in better credibility

$H1_1$ = Experience and Information asymmetry have nothing to do with credibility

Table 11: Finfluencer Credibility score

S.No.	Finfluencer	IAS	Exp	Credibility Score
1	Investor's Clinic	0.05	1.1	0.733333333
2	Stock Market India	0.05	0.4	0.642105263
3	CA Rachana Ranade	0.033333333	1.6	0.638596491
4	Nikhil Kamath	0.05	0.1	0.638596491
5	Anurag Aggarwal	0.033333333	1.6	0.547368421
6	Ankur Warikoo	0.05	0.7	0.543859649
7	Moneycontrol	0.033333333	1.9	0.515789474
8	FinnovationZ by Prasad	0.05	1	0.421052632
9	Geojit Spotlight	0.05	1.4	0.385964912
10	CA Rahul Malhod	0.033333333	0.2	0.385964912
11	Stock Pro	0.033333333	0.8	0.326315789
12	Savvy Investor	0.05	0.4	0.326315789
13	Finance with Vineet	0.033333333	0.3	0.231578947
14	Pranjal Kamra	0.033333333	1.3	0.228070175
15	Groww	0.033333333	0.8	0.196491228

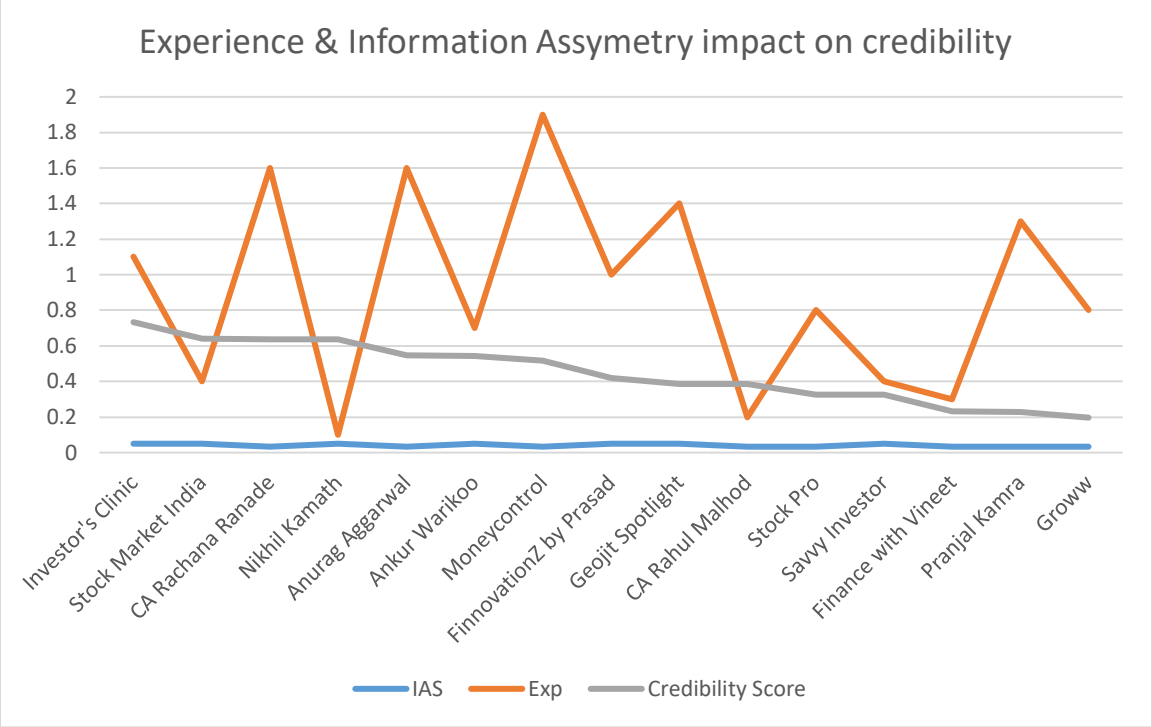


Figure 4: Credibility Hypothesis H1

From the above graph, we can clearly see that there is no correlation between said values hence we can safely reject $H1_0$ and accept $H1_1$.

Impact of Finfluencer Media Dominance: The hypothesis is that higher social proof and emotional appeal to viewers impact investors' beliefs more.

$H2_0 =$

$Higher\ social\ proof\ and\ emotional\ appeal\ score\ results\ in\ investor\ attention$

$H2_1 =$

$Social\ proof\ and\ emotional\ appeal\ results\ has\ no\ impact\ on\ investor\ attention$

Table 12: Media Effectiveness

S.No	Finfluencer	SPS	EAS	Investor Attention
1	Investor's Clinic	0.00041097	0.33766756	0.050752877
2	Anurag Aggarwal	0.00094016	0.3118799	0.047017025
3	Stock Pro	0.00131323	0.194	0.029428308
4	Groww	0.00068476	0.1925	0.029046189
5	FinnovationZ by Prasad	0.00053797	0.18529412	0.027928611
6	CA Rachana Ranade	0.00056331	0.18125	0.027328327
7	Finance with Vineet	0.00172037	0.17610966	0.026846541
8	Pranjal Kamra	0.00080274	0.17125	0.025888186
9	Moneycontrol	0.00013335	0.17222222	0.025866671
10	CA Rahul Malhod	0.00030245	0.16428571	0.02471847
11	Savvy Investor	0.00081846	0.16219512	0.024533884
12	Ankur Warikoo	0.00034994	0.158	0.023787484
13	Geojit Spotlight	0.00027737	0.15357143	0.023105056
14	Stock Market India	0.00071678	0.15266667	0.023079196
15	Nikhil Kamath	0.00033531	0.153	0.023033828

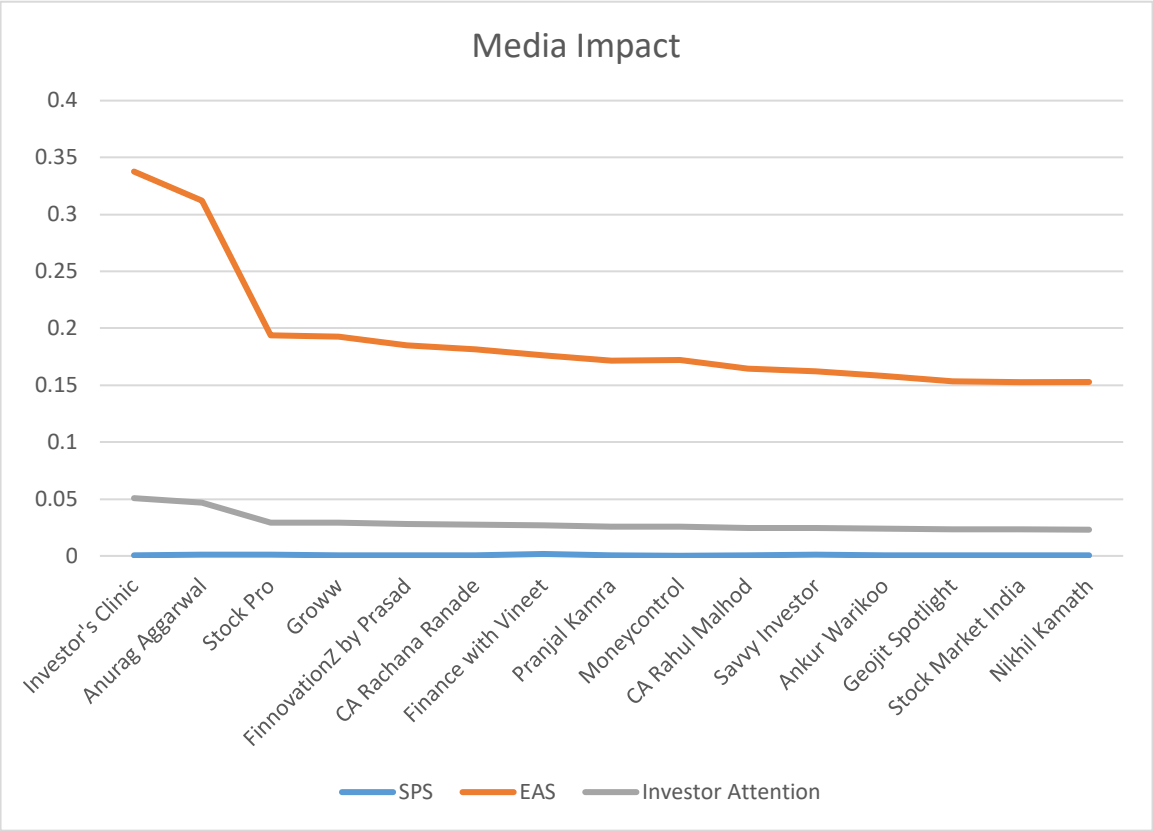


Figure 5: Viewer Attention Hypothesis

From the above graph, we can clearly see that Investor attention is related to Engagement Score or EAS therefore we can safely accept $H2_0$ and reject $H2_1$.

Impact of Content Posted. The hypothesis is that better investment opportunities or FOMO creation results in higher viewer attention and belief.

$H3_0 =$

$Higher\ investment\ opportunities\ and\ FOMO\ created\ results\ in\ investor\ attention$

$H3_1 =$

$Investment\ opportunities\ and\ FOMO\ created\ has\ no\ impact\ on\ investor\ attention$

Table 13: FOMO relation to Investor Attention

S.No	Finfluencer	FOS	Investor Acceptance
1	Stock Pro	2.52	1.836
2	Anurag Aggarwal	2.4	1.8
3	Geojit Spotlight	2.7	1.49
4	Finance with Vineet	2.1	1.43
5	Pranjal Kamra	2.7	1.37
6	Savvy Investor	2.25	1.235
7	Ankur Warikoo	2.4	1.04
8	Investor's Clinic	1.2	0.92
9	Nikhil Kamath	2.4	0.92
10	CA Rahul Malhod	2.4	0.88
11	Groww	0.9	0.87
12	CA Rachana Ranade	2.1	0.83
13	Stock Market India	2.1	0.79
14	FinnovationZ by Prasad	1.8	0.78
15	Moneycontrol	1.2	0.52

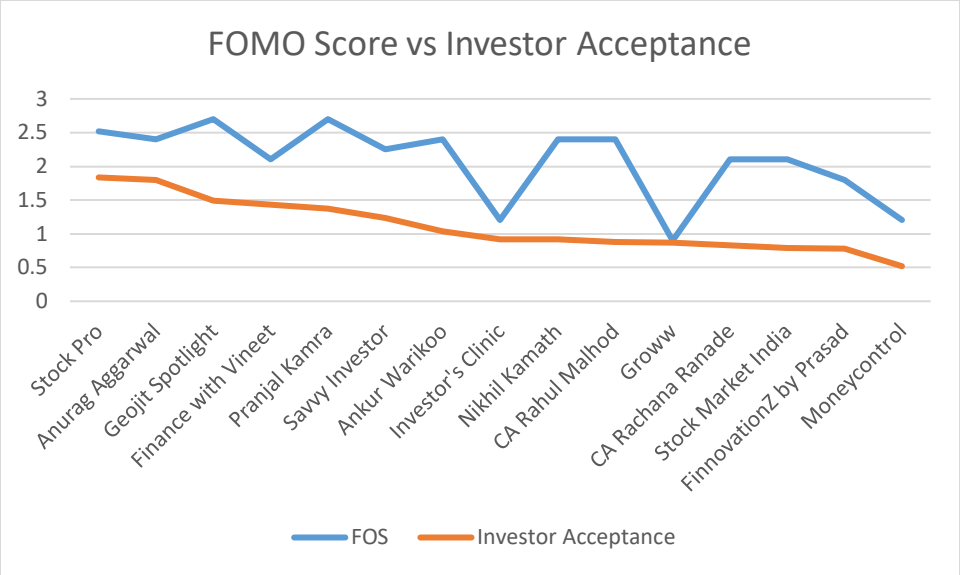


Figure 6: FOMO Score vs User Acceptance Hypothesis

From the above graph, we can clearly see that investors accept the advice when Fear is created in the delivered media content therefore we can safely accept $H3_0$ and reject $H3_1$.

Investor Analysis:

Impact of Age on Investment. Does age have any impact on the longevity of investment that a person makes?

$H4_0 = Older\ investors\ have\ larger\ investment\ horizons$

$H4_1 = Young\ investors\ have\ larger\ investment\ horizons$

Table 14: Investment Horizon For Age Groups

Age Brackets	IH < 1 year	IH 1-3 Year	IH 4-6 Year	
<20	1	5	3	**9**
20-30	17	20	26	**63**
31-50	55	47	26	**128**
>50	1	1	1	**3**
	74	**73**	**56**	**203**

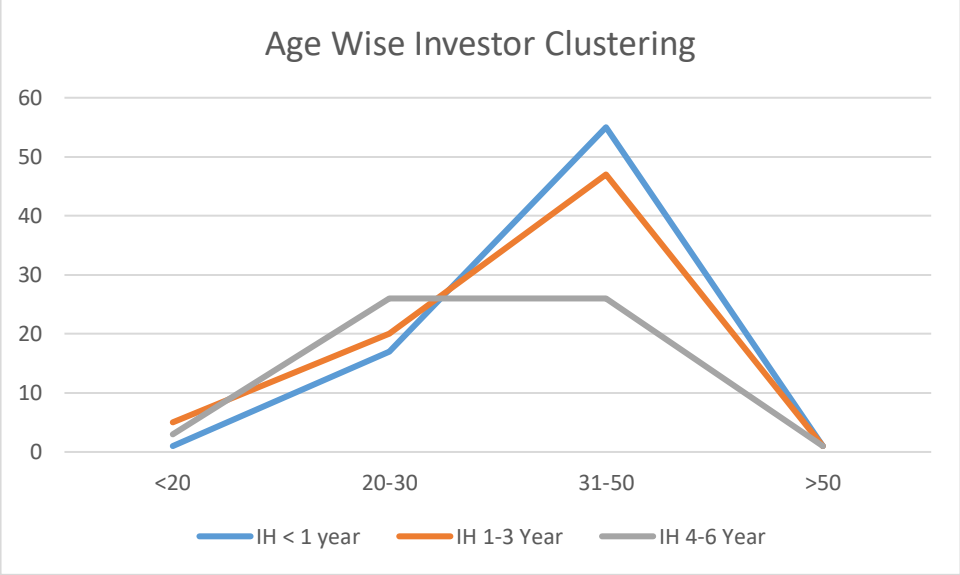


Figure 7: Age Group and Investment Horizon Hypothesis

From the above graph, we can clearly see that the age group 31-50 considers all investment horizons while investors less than 20 years or more than 50 years do not invest

more. Age Group 20-30 invest more in long tenure, therefore, we can safely accept $H4_0$ and reject $H4_1$.

Impact of Gender on Investment. Do males have higher investment horizons than females?

$H6_0 = Males\ remain\ invested\ for\ longer\ time$

$H6_1 = Gender\ has\ no\ relation\ with\ investment\ horizons$

Table 15: Gender impact on Investment Horizon

Gender	IH < 1 year Total	IH 1-3 Year Total	IH 4-6 Year Total	IH > 10 Year Total
Male	62	114	93	31
Female	14	42	46	9

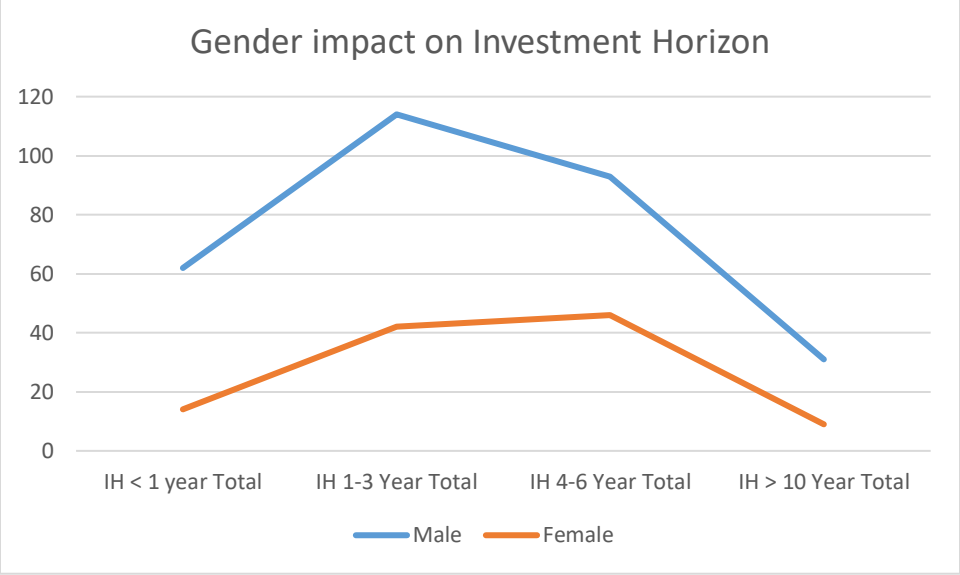


Figure 8: Gender Impact on Investment Horizon

From the above graph, we can clearly see that Females normally spend for 4 to 6 years of time horizon, whereas males invest more with 1 to 3 years of time frame. Overall it is safe to say that Males remain invested for a longer duration compared to females. Hence it is safe to accept the Hypothesis $H6_0$ and reject $H6_1$.

Financial News Gathering:

I have observed news generated for 1198 investment opportunities out of which 233 investment assets had meaningful news. These news have the following observations.

Table 16: Average of biases in news observed on a particular day

Confirmation Bias	Availability Bias	Framing Bias	Simplification Bias
225	220	214	216
8	13	19	16

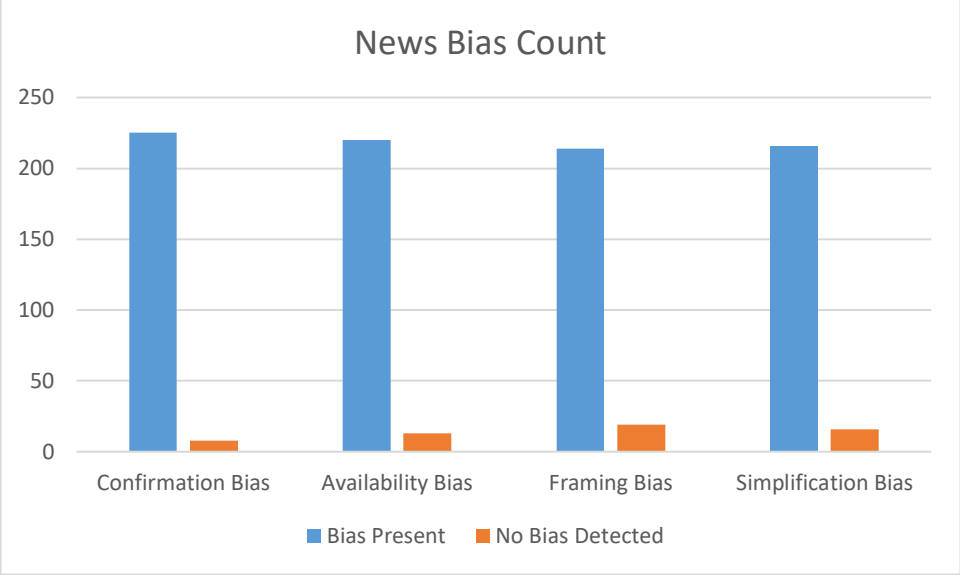


Figure 9: Presence of Bias

Investors Clustering:

For every 2000 investors, I observed the following plots. A set of 7 data points were observed, namely Cost Basis, Market Value, Unrealized Gains, Dividend Yield, Capital Gains, Sharpe Ratio and Investment Horizon. The following figure is a representation of data distribution of the last six months for 14 sample investors.

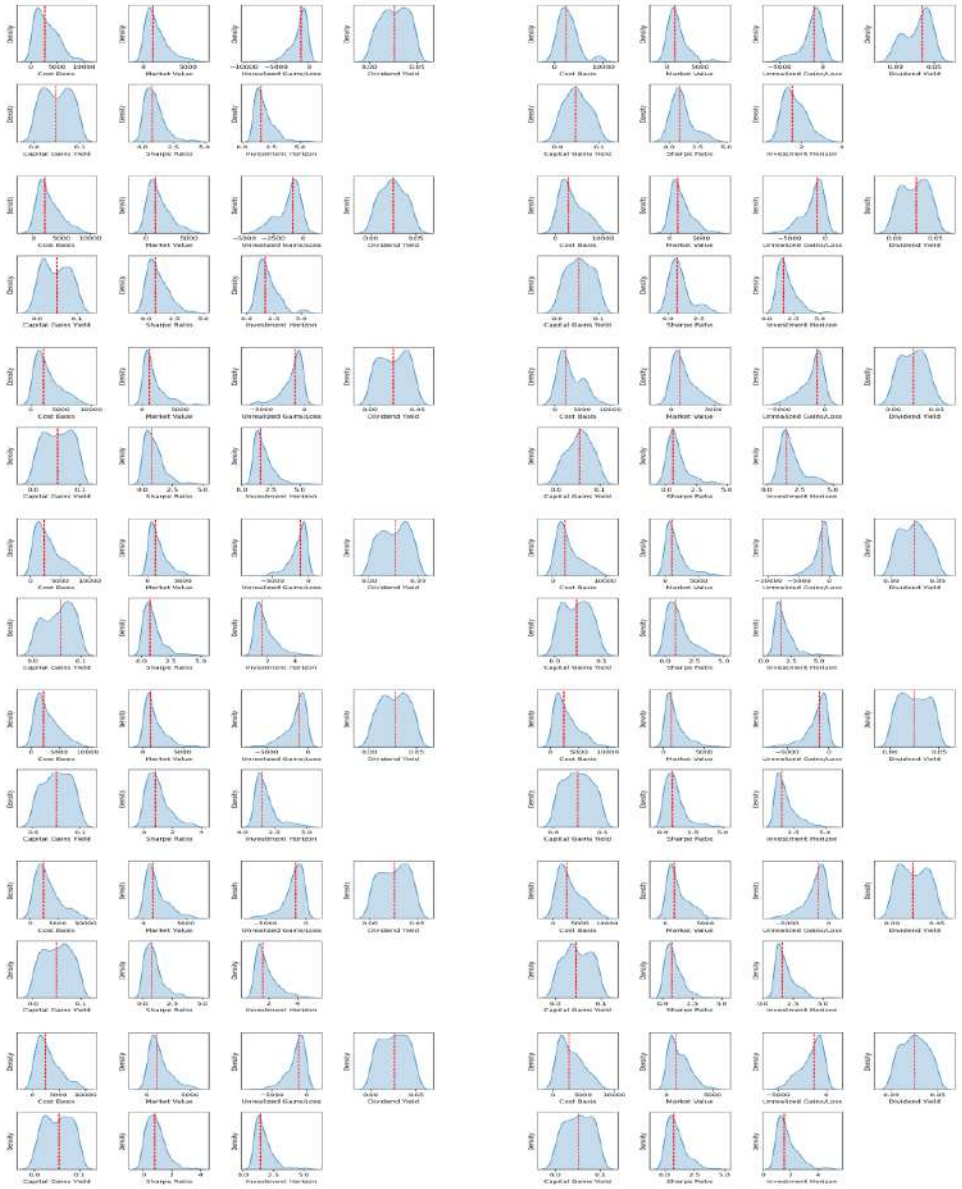


Figure 10: Investor Datapoints

Figure 9 represents characteristics of the portfolio which are useful to define user behaviour. Each of the investor portfolios can be classified as “Under Risk” or “Under Loss” or “Profitable”.

1. **Under Risk:**
    a. Unrealized Loss: The investor has a negative unrealised gain/loss, indicating potential investment choices that have lost value. This suggests a willingness to take on investments with higher risk.
    b. High Sharpe Ratio: The Sharpe Ratio is relatively high. While this indicates good risk-adjusted returns, it also implies that the investor might be taking on more risk to achieve those returns.
    c. Investment Horizon: Shorter investment horizons often correlate with higher risk tolerance, as investors may be more willing to accept short-term volatility for potential gains.
2. **Under Loss:**
    a. Significant Unrealized Loss: The most prominent factor is the substantial negative "Unrealized Gains/Loss". This indicates that the current market value of the investor's portfolio is significantly lower than the initial cost basis, resulting in a substantial unrealized loss.
    b. High Sharpe Ratio: A High Sharpe Ratio, along with Significant Unrealized Losses indicates strong risk-adjusted returns.
3. **Profitable:**
    a. Positive Unrealized Gains/Loss: This is the most fundamental characteristic. A profitable portfolio should show an increase in value compared to the initial investment.

b. High Sharpe Ratio: A Sharpe Ratio greater than one generally indicates that the portfolio generates returns over the risk-free rate. A higher Sharpe Ratio signifies better risk-adjusted returns.
c. Positive Dividend Yield: While not always the primary driver of returns, a positive dividend yield contributes to overall portfolio income.
d. Strong Capital Gains Yield: Consistent capital appreciation is crucial for long-term portfolio growth.
e. Aligned with Investment Horizon: The investment strategy should align with the investor's time horizon. Long-term investors can generally tolerate more volatility, while short-term investors may prioritize capital preservation and liquidity.

Clustering based on various parameter

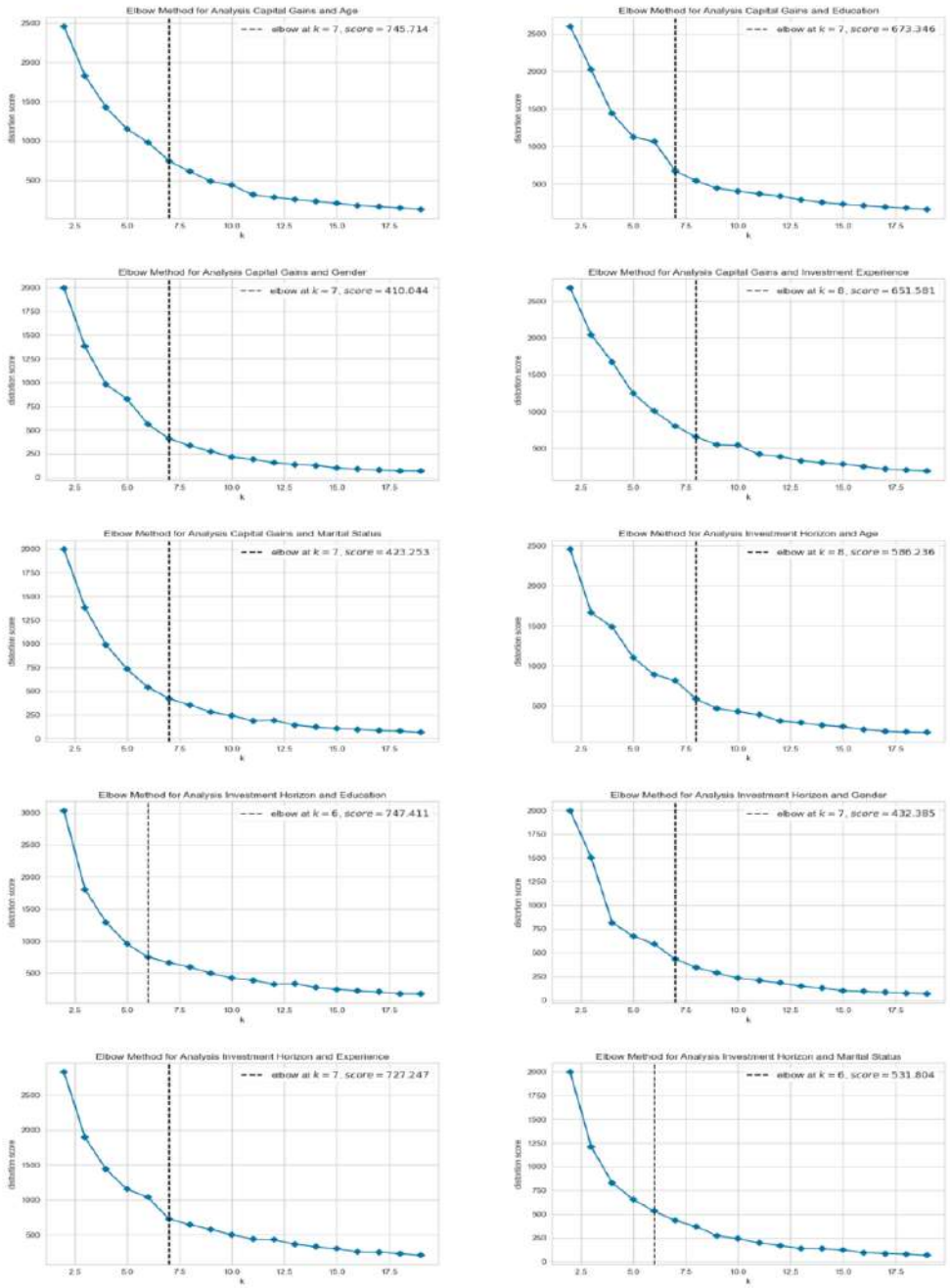


Figure 11: K-Means Clustering for investor data

From Figure 10 it is evident that the ideal clusters could be 7 for representing the investor population. The following are the cluster strategies:

Table 17: Clustering Strategies

Sharpe Ratio	Investment Horizon	Financial Education	Investor Experience	Marital Status	Age	Cluster Remarks
Low	Long	Moderate	High	Married	High	Conservative Investors
High	Short/Mid	Moderate/ High	Moderate	Married/Unmarried	Medium	High-Growth Investors
High	Short/Mid	Moderate/ High	Moderate	Married	Medium /High	Income-Oriented Investors
Moderate	Very Short/Short	Low/Moderate	Low/Moderate	Married/Unmarried	Low/Medium	Short-Term Traders
Moderate	Long	High	High/Moderate	Married/Unmarried	Medium /High	Long-Term Value Investors
Low	Short/Mid	Low/Moderate	Low/Moderate	Married/Unmarried	Moderate/High	Low-Risk, Low-Return Investors
High	Short/Mid	Moderate/ High	High	Unmarried /Married	Medium /High	High-Risk, High-Reward Seekers

Placement of a new user in one of the above clusters requires a questionnaire and a sneak peek into their investments if they agree to share. Based on the above analysis in

Figure 10 and Table 17 following questions can be asked to classify users in one of the 7 clusters:

1. What are your primary financial goals for this investment?
    a. Retirement savings 3
    b. Down payment on a house 5
    c. Child's education 4
    d. Generate income 1
    e. Wealth preservation 2
2. If you are married does your partner also prefer in investing?
    a. Married and yes both of us invest 3
    b. Married but only I invested 2
    c. Unmarried 1
3. When do you anticipate needing to access this money?
    a. Short-term (within 1-3 years) 1
    b. Medium-term (3-5 years) 2
    c. Long-term (5+ years) 3
4. How comfortable are you with possibly losing some or all of your investment?
    a. Very comfortable 1
    b. Somewhat comfortable 2
    c. Neutral 3
    d. Somewhat uncomfortable 4
    e. Very uncomfortable 5

5. How would you describe your investment experience?
    a. Beginner 1
    b. Intermediate 2
    c. Experienced 3
6. Which of the following best describes your investment approach?
    a. Aggressive (high growth, high risk) 1
    b. Moderate (balanced growth and risk) 2
    c. Conservative (low risk, low growth) 3
7. Are you interested in generating income through dividends?
    a. Yes 3
    b. No 1
    c. Somewhat 2
8. Do you prefer to invest in companies that are socially and environmentally responsible?
    a. Yes 3
    b. No 1
    c. Neutral 2
9. What is your current age?
    a. <20 0.2
    b. 20-30 0.6
    c. 31-50 0.9
    d. >50 0.1

Cluster Score is defined as the Weighted sum of all the above answers. The importance of features decides the weights.

$S1 : Score\ of\ Answer\ to\ Question\ 1\ \ W13 : Weight\ related\ to\ answer = 0.1$

$S2 : Score\ of\ Answer\ to\ Question\ 1\ \ W14 : Weight\ related\ to\ answer = 0.3$

$S3 : Score\ of\ Answer\ to\ Question\ 1\ \ W15 : Weight\ related\ to\ answer = 0.8$

$S4 : Score\ of\ Answer\ to\ Question\ 1\ \ W16 : Weight\ related\ to\ answer = 0.5$

$S5 : Score\ of\ Answer\ to\ Question\ 1\ \ W17 : Weight\ related\ to\ answer = 0.4$

$S6 : Score\ of\ Answer\ to\ Question\ 1\ \ W18 : Weight\ related\ to\ answer = 0.3$

$S7 : Score\ of\ Answer\ to\ Question\ 1\ \ W19 : Weight\ related\ to\ answer = 0.2$

$S8 : Score\ of\ Answer\ to\ Question\ 1\ \ W20 : Weight\ related\ to\ answer = 0.3$

$S9 : Score\ of\ Answer\ to\ Question\ 1\ \ W21 : Weight\ related\ to\ answer = 0.6$

$$classification\ score = (S1 * W13) + (S2 * W14) + (S3 * W15) + (S4 * W16) + (S5 * W17) + (S6 * W18) + (S7 * W19) + (S8 * W20) + (S9 * W21)$$

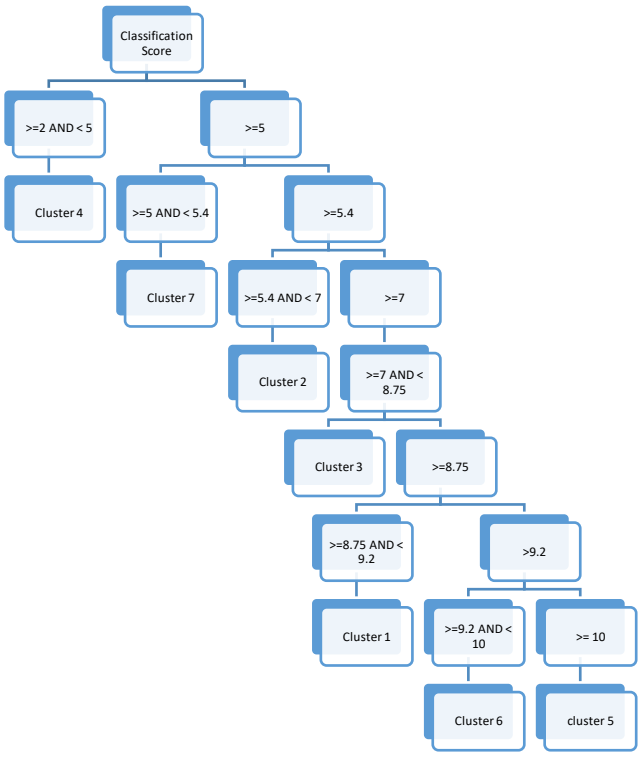


Figure 12: Decision Tree for User Clustering

The decision Tree in Figure 11 was tested on four users, and the results depicted their behaviours well.

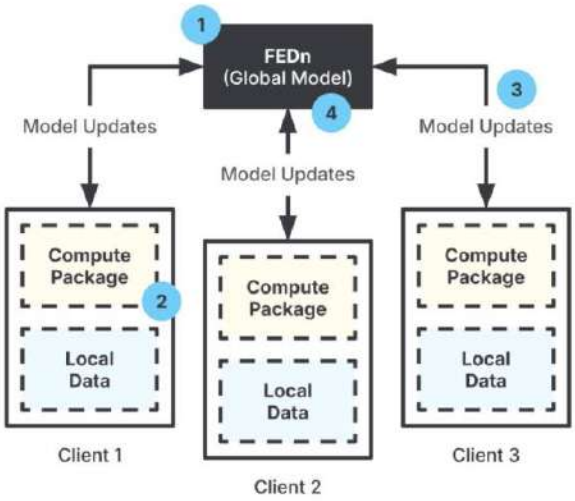
Table 18: Test for clustering

Name	Age	Profession	Cluster Identified	Remark
User 1	68	Retired Principal	Cluster 2 - High-Growth Investors	Afraid of investment hence remain invested for moderate term. Invest wisely and follow news.
User 2	67	Retired Teacher	Cluster 3 - Income-Oriented Investors	Short term investor with moderate experience, follow market sentiment.
User 3	17	Student	Cluster 2 - High-Growth Investors	Short term investment for Vacations and Leasure

User 4	39	House Maker	Cluster 5 - Long-Term Value Investors	Moderate experience in investments, High education with Longer horizons

Propagating model using FML:

For each cluster, I have used SEM models with FML, which can be used to filter news. Such Models can constantly evolve to make it more accurate and adapt to new physiological cues.



FEDn Model Update Flow

1. First global model (=seed model) is sent to clients (Model Updates)
2. Clients receive the global model and update it based on their local data. For this, FEDn accesses the code in the compute package
3. Clients send back their local model parameters (Model Updates)
4. FEDn aggregates them to a new global model

This process is repeated for a given number of rounds.

Figure 13: Scaleout Fedn Flow

Figure 12 describes how models update themselves with local data. In my research, local data comprises of:

1. Investment profile consisting of investment behaviour analysis traits
2. Portfolio Analysis
3. Finfluencers research done by investor
4. Digital news content referred by investor

The seed model is capable of identifying FMCS, however, based on the output and investor feedback, the model gets retrained and the adjusted weights are sent back to the central server. This update from clients leads to better seed models.

3.9 Research Design Limitations

Investor Truthfulness:

A fundamental concern when examining investment behavior is the commitment of truth by participants. For a variety of social reasons, investors may have a hard time disclosing their actual risk attitude, investment patterns, and even previous financial activities. Such unwillingness or inability to reveal the whole true self can lead to information and sometimes even systematic biases.

The participant borders a fine line between desired outcomes and negative self-portrayal. It is also possible that he or she gives good answers to inappropriate questions such as the actual investment involvement or sociological interest towards investment ethics.

These biases do matter since they pose a risk to the research assumption and outcome of it. Researchers must employ strategies to mitigate these challenges, such as ensuring anonymity, using indirect questioning techniques, and carefully considering the potential impact of social desirability bias on participant responses.

ImMatured Responses:

Investment education should be able to empower people effectively and this concern must be taken seriously in every investment decision. Nonetheless, investment education has traditionally struggled in penetrating and appealing a generally widespread audience. There are numerous investment education materials that are complicated, full of jargon, and lack clarifying explanations from an already existing context in investing. Besides, the materials could also fail to be rich, interesting, and engaging learning experience, which is appealing to a wide range of audiences.

For instance, let’s take a few people who are figures in society; some of them would say investment seminars are boring and can hardly consolation reading investment

texbooks, and the others whom without investment gaming would find it hard to understand financial literacy.

To bridge this gap, investment education needs to be enhanced using these cutting-edge technologies, customization, and behavioral strategies such that the investment knowledge is interesting and easy for everyone.

Finfluencers Influence:

Understanding behavioral digression poses a significant challenge because of the over-reliance on the finfluencers content and beliefs. The investor, especially the younger investors, tend to use social media as a primary source of information for their investment decisions which is in most cases misplaced in favor of investors with no financial qualifications. This creates an opportunity and risk of bias, divergence and sorting as the finfluencer content may be tailored to appeal to the specific audience as opposed to sound financial advice. The consequences stemming from reliance on social media content are herb behaviour, increased market abuse, and gaps in credibility emerging to the point where virtues are entirely trashed.

Regulatory Checks:

Understanding the investor behaviour in INDIA is not an easy task because of the regulatory environment and the issue of ‘captive knowledge’. More government control and strict data protection regulation can make this disaggregate data inaccessible which makes the pre-defined ideal sample of the Indian population comprehensive and representative. Moreover, there is also the problem of self-selection bias, because of dependence on self-selected participation, which introduces an entirely different set of investment behaviour characteristics. This creates problems for the representativeness of certain investor groups which leads to correctness of the research.

For instance, financial markets tend to be under-represented in research studies by less skilled and interested individuals which results in a sample that lacks active and informed investors.

Innovation, ethics, and collaboration with government and financial institutions are necessary in designing appropriate research along with data collection techniques to avoid such mistakes that would pave the way for mitigating these challenges.

Federated Machine Learning Updates:

Despite deep learning models being a great asset in investor behavior analytics, there are some problems that arise. One such challenge is that investment behavior models are developed and executed based on historical data, which is a double edged sword. These may not provide sufficient information on how investors would react to market changes. Another issue is over flooding, in which using previously available models produces out done results in poorly received data. Lastly, in investment behavior, the lack of understanding of the psychosocial factors combined with market forces makes the term "predicting" the model's results rather vague and leads to misunderstanding. Furthermore, these methods lack ethical values in regards to their usefulness in predicting markets and investing, which in turn invites the idea of algorithm discrimination against other markets.

3.9 Conclusion

In this research, I analyzed the influence of finfluencers on readers' investment choices, considering YouTube videos and news articles, while creating unique methods of detecting and countering such content..

Key findings are:

1. Development of a "Manipulative Score": I constructed a SEM (Structural Equation Model) to gauge the level of manipulation of an individual piece of finfluencer content where the emotional appeal of the finfluencer, persuasive language, and disclosure practices served as independent variables
2. Investor Clustering: Seven different groups were created based on the individual investment styles of the investors – some groups were called "High-Growth Investors," "Conservative Investors," etc.
3. Federated Learning for Personalized Filtering: Each of the investor groups were assigned a unique news filtering system developed using federated learning. It enabled building local models without compromising data privacy.
4. Enhanced Investment Decision-Making: Investors can exploit the "Manipulation Measure Score" together with the filter and receive true and unmanipulated quality content with the aid of the 'Manipulation Measure Score.

The incorporation of sophisticated analytical methods like SEM and Federated Learning with segmentation of investors can help in promoting financial literacy and allowing investors to make better as well as unbiased investment choices. This paper highlights the extent to which this combination can be useful.

CHAPTER IV:

RESULTS

4.1 What kind of bias in the investment information may impact an investor's decision-making?

In my research aimed to identify the types of bias in investment information that can significantly impact an investor's decision-making. Key findings suggest that investors are susceptible to various biases, including:

1. Confirmation Bias: Investors tend to give preference to information that support their beliefs and disregard anything that proves otherwise.
2. Herd Mentality: prone to being influenced by other people's investment decisions which can lead to reckless behavior in the markets.
3. Availability Bias: Investors tend to over or underestimate the possibility of events that are reported by the media more often, regardless of their statistical nature. For instance, the recent news of an IPO being successful is likely to lead to increased investments without much analysis due to overestimated potential returns.
4. Loss Aversion: Due to high sensitivity towards negative potential returns, investors are likely to shy away from investments as they become resistant to taking up higher potential investment returns due to high associated risks.

Such biases significantly harm investment goals and can lead to poor portfolio contribute to inefficient aggressive investment and eventual returns diminishes. In order to make sound investment decisions, careful measures to identify and eliminate such biases are a must.

4.2 Are the identified biases present in highly valued finfluencers over YouTube or online Blogs?

During my studies, I tried to assess the scope and influence of the manipulation tactics that financial influencers use across the various platforms. A novel approach was undertaken whereby structural equation modeling (SEM) and Federated Machine Learning were used in tandem.

The creation of "Manipulative Score": A sophisticated "Manipulative Score" was created using an SEM model that examined the content of several finfluencers and their biases within influencer content. Thoroughly included behavioral traits such as Sophisticated exploitation of follower's psychology incorporating herd and confirmation bias.

1. Behavioural Traits: The exploitation of an individual's pre-existing knowledge and information of the particular subject without any additional context.
2. Information Asymmetry: Manufacturing an individual's perception of knowing possess expert skills and knowledge.
3. Perception of Expertise: Creating an illusion of authority and expertise.
4. Social Proof: Showcasing the popularity of the investment and the success of others who have already invested.
5. Emotional Appeals: Evoking emotions such as anxiety, greed or urgency to act upon investment decisions
6. Fear of Missing Out (FOMO): Promoting fear of losing out on the possible opportunity to invest or gain benefits
7. Availability Bias: Skewing the interpretation of information that is newly encountered or is easy to obtain.

The finances sector impersonates manipulative appeal and aids in highlighting the numerous issues this poses comprehensively. This information has been considered useful from a manipulative content perspective. This set of knowledge has the capability to assist investors in making better decisions that are objective and unbiased by working on the principle of sharing limited but highly useful information to the targeted audience.

4.3 What are the common behavioural traits that exist in INDIAN investors?

My objective was to analyze the effects of certain demographic traits like gender or age coupled with investment horizon, to determine common behavioral traits among Indian investors. The analysis revealed the following key findings:

1. Gender Disparities in Investment Horizons: The research revealed that investment horizons differ among males and female investors in distinct ways. On average, females appeared to favor long-term investments, which are usually considered to be around 4 to 6 years. Males on the other hand, were found to prefer short term investments, with an investment horizon of 1 to 3 years being the most common. These findings imply that males tend to pursue more short term or speculative investments than females.
2. Age-Related Investment Behavior: The diversity among age groups can give more insight into variability in investment behaviors as demonstrated the following example. The study showed a distinct difference when an investment horizon of 31 -50 years was taken into account. Investors in between 31-50 years showed a greater diversity in investment horizons, as they looked at investments of all time ranges. In comparison younger (below 20 years) and older (above 50 years) investors had a limited range of investment horizons,

which may have been a result of limited finances, greater risk aversion or life stage goals.

These results are the most important for understanding the many ways of investing that exist within Indian investors. Financial institutions, policy makers, and even the investors themselves will be better informed with these behavioral patterns.

4.4 How much is AI and ML impacting investment decision-making, i.e. How much of Digital Technology impact investment decision-making?

As part of my work, I address the influence of AI and ML technologies in investment decision making. This study was designed to determine the degree to which these technologies are evolving the investment sphere using the safe and distributed architecture of Federated Learning (FedML) as a backbone. A few noteworthy advantages that were uncovered include:

1. Enhanced Investment Decision-Making: The utilization of AI/ML increases the effectiveness of making investment decision as follows:
    a. Improved Risk Assessment: Algorithms can Scan huge sets market data, coverage, and economic data on news to pinpoint pros and cons for a given investment with more accuracy and less fuss than existing practice allows.
    b. Portfolio Optimization: AI-based tools can accurately allocate investment portfolios based on the specified risk tolerance, objectives, and limitations of each investor.
    c. Predictive Analytics: Algorithms of machine learning can be exploited to project victories and defeats in negotiation markets, spot possible bargain purchases, and estimate the performance of various assets.
    d. Algorithmic Trading: Trading algorithms powered by AI can perform trades at great speeds and large volumes, exploiting market gaps and producing profitable returns.

Advantages of Federated Learning:

1. Data Privacy and Security: With FedML, it is possible to train models while keeping sensitive data of investors private and secure. This eases the privacy fears and regulatory issues.
2. Improved Model Performance: FedML can help construct AI/ML models applicable to investment decision making that are stronger and more accurate by combining data from different sources without violating personal privacy.
3. Enhanced Trust and Transparency: Using FedML's distributed architecture increases the level of trust and transparency in the use of AI/ML in the financial sector.

This document also demonstrates the impact and predictions of sAI/ML technologies on the investment world. While using those technologies in the industry, frameworks like FedML ensurses data privacy and security, which enables the financial sector to embrace propelling artificial intelligence technology, leading to better ways of serving investors with reliable and effective investment strategies.

4.5 Summary of Findings

This study was focused on several aspects of Indian investor behavior including the influence of biases, finfluencers, demographic factors, and the impact of AI/ML technology. The following points were derived from the study.

1. Investor Biases:
    a. Overconfidence bias and confirmation bias were identified as some of the critical biases that impact the decisions of investors.
    b. Further, content that is written by finfluencers is highly valued on social media such as Youtube and blogs, and these active bloggers have an overwhelming amount of unconstrained powerful follower bases.
2. Investor Demographics:

    Observed significant variations in investment behaviour across different demographic groups, such as:
    a. Gender differences in investment horizons portray that women generally have longer-term horizons as compared to men.
    b. Aged 31-50 years of investors seem to be the most active investors because younger and older people have fixed investment horizons.
3. Impact of AI/ML:

    While investment decision making is core to Ai/ML technology, the subsequent areas of investment risk assessment, portfolio management, and predictive analytics are even more significant areas impacted by AI.

With the onset of AI in finance, a new modern day concern of data security emerged. Allowing a multilayered approach to AI/FedML can significantly enhance privacy along with security.

4.6 Conclusion

This research has contributed to understanding the behavioral trends of economic investors in India, incorporating the aspects of bias and the role of AI/ML technologies. This chapter aims to examine the role of social media in serving as an effective educational tool in India, with the goal to analyze the impact biases have on investors, how 'finfluencers' play a part in it, and if AI/ML technologies are amplifying these biases. There are few areas identified as potential gaps as follows :

1. Bias Mitigation: There is little understanding of how biases in finfluencer content can be mitigated and what appropriate information standards will ensure a better management of investor relations.
2. Investor Education: Determine which type of financial education initiatives might help bolster investor biases and illiteracy..
3. AI/ML Development: Determine which type of financial education initiatives might help bolster investor biases and illiteracy..
4. Regulatory Implications: Examine the possible consequences arising from the increasing use of AI/ML within the financial ecosystem, including the considerations for appropriate ethical principles and self-regulation.
5. Cross-cultural Comparisons: Rather than composition, focus on broad descriptions of the patterns and trends of investment behavior among different people across cultures and socio-economic backgrounds.

Understanding investor behavior in India, is extremely interesting and is explored in this research. Further research and development is needed to meet the new challenges and changes in the Indian financial market..

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

The information presented highlights the significance of further investigations into the associations between investing behaviors and their potential determinants for effective financial literacy programs and investment services. My study also looks at the multi-dimensional impacts of finfluencers on investors' decision-making processes and addresses the risks that may arise through biased information. My study informs regulators like SEBI on how these institutions could strengthen the regulation of harmful content by:

1. Finfluencer Content Analysis: Future research should investigate the prevalence of biases (e.g., confirmation bias, overconfidence bias, herding bias) in the content generated by prominent finfluencers in India.
2. Analysis of Investor Behavior: Analyze the impact of finfluencer content on investor decision-making, including the extent to which it influences investment choices and risk-taking behaviour.
3. Development of Bias Detection Tools: Develop AI-powered tools to identify and flag potentially biased or misleading content in finfluencer messages.

The aim of this study is to provide a tool to investor's to evaluate market news and events for their true impact on their investment goals. This study is broaddy divided into 3 parts:

a. Study of news and social media for Manipulative Scores
b. Study of investors' demography and behaviour towards investments in INDIA

c. Use of FML to deploy models that can filter news based on investors' behavioural cluster

This study creates 7 clusters of investors based on their attributes and tries to filter news for them. The news is then presented to investors, and they may choose to invest or reject the news. The success of this research relies on how much news gets really accepted or translated into investment decisions.

5.2 Discussion of "What kind of bias in the investment information may impact an investor's decision-making?"

As discussed with couple of investors with various demographies following are the important categories of news that majorly impact their investment decisions:

1. Political News:
    i. Government stability: Political instability can create uncertainty and discourage investment
    ii. Election results: Election outcomes can significantly impact investor sentiment, depending on the perceived economic policies of the winning party
    iii. Geopolitical events: News about international relations, trade wars, or geopolitical tensions can impact investor confidence and market volatility
2. Corporate News:
    i. Company performance: News about a company's earnings, new product launches, or mergers and acquisitions can directly impact its stock price
    ii. Industry trends: News about technological advancements, changing consumer preferences, or industry disruptions can influence investment decisions across sectors
3. Global News: Global economic conditions: News about global economic growth, interest rates, and financial markets can have a significant impact on Indian markets due to their interconnectedness with the global economy.

However, the Source of news, its credibility and investors' way of interpreting it is really important to see the true impact of news on investors.

5.3 Discussion of "Are the identified biases present in highly valued finfluencers over YouTube or online Blogs?"

News has always been constructed, whether it is delivered through the traditional forms of the media, online platforms such as YouTube, or written articles and blogs. The selection of plots, framing of events, the language used, and even the preface or presentation sequences plays a pivotal role in how people perceive them. While this constructs thematically categorizing news aids in effective information transfer, it unavoidably brings in personalization. This shows us how finfluencers are even more charismatic due to the amplifying factor that comes through elocution. Transformational leadership through emotional appeals, and creating personal credibility are some of the tactics that could possibly be used by finfluencers to change the audience's investment choices decision.

Even though these strategies can make the content memorable and relatable, there are higher chances of a manipulative bias occurring. News and financial consumers should be careful of these built in biases and assess the information critically, taking into consideration which sources is relaying the information together with their potential motivations and particulars of the environment with the entire context.

Essentially, it is safe to assume that the absolute unbiased reporting of news is nearly impossible to attain. From the selection and the manner of the information being put out to the public, there is always some level of influence the audience's understanding of the information will be openn.

5.4 Discussion of "What are the common behavioural traits that exist in INDIAN investors?"

The common behavioral characteristics in INDIAN investors are as below:

1. Risk Aversion: Many Indian investors exhibit a degree of risk aversion and prefer to invest in comparatively safer instruments such as gold, real estate, or fixed deposits than in more risky stocks.
2. Herd Mentality: Many Indian investors act more or less like sheep as they are prone to panic selling and stock chasing during market slumps and booms respectively.
3. Emotional Investing: There are emotions of fear, greed and regret, which affect most investment decisions and as a result most people act impulsively reaching unplanned investments.
4. Focus on Short-Term Gains: Short term benefits are reported to be emphasized over long term wealth creation by most Indian investors. This could result in over trading and not being able to cope with market changes.
5. Preference for Familiar Investments: Investments Setting Focus: Investors tend to prefer putting money into firms or industries that they are used to instead of financially viable investments.
6. Growing Interest in Equity Markets: Increasing Appetite for Equity: The general aversion to risk still remains, but there is an increasing appetite for equity, especially among the young generation, which is attributed to the increase in financial education and the availability of digital resttlg platforms.

5.5 Discussion of "How much is AI and ML impacting investment decision-making, i.e. How much of Digital Technology impact investment decision-making?"

AI and ML are making a significant impact on investment decision making in many areas. These technologies allow for the processing of large volumes of data and the recognition of sophisticated patterns and trends that may not be noticed by human analysts. This results in improved forecasting of market moves, more accurate risk calculations, and better portfolio management. For instance, algorithms using AI can scan news articles, determine public sentiment about businesses, track social media communication, track economic movement indicators, and predict stock price movements. AI can also tailor investment strategies to suit particular clients, including their investment objectives and risk profiles.

In this context, federated machine learning has a lot of advantages. First, it enables joint collaboration of several businesses or people in training machine learning models while keeping their source raw data private. This level of confidentiality is a prime concern in the financial sector. Second, it increases model performance in terms of accuracy and robustness due to the mixed data received from several locations. Lastly, as data distributed systems or individual devices or systems perform the bulk of data processing and model training, federated learning has an edge over traditional centralized systems. With model training occurring within the data's locale, less data storage and transfer is required in a core position, making it more beneficial.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The objective of this research was to develop an innovative framework for delivering financial news which takes the privacy of an investor into consideration while improving the quality of the investment decision. The goal of the research was through Federated Machine Learning (FedML) to develop a mechanism which filters news articles according to the profiles of individual investors..

Key Components:

1. Investor Segmentation: A detailed study of Indian investors' demographics and their investment or underwriting behavior namely risk bearing capacity, time duration within which the investment is done, and the class of assets preferred. The analysis led to the formation of seven highly differentiated investor segments each having distinct characteristics and preferences on investment.
2. News Analysis and Sentiment Scoring: The relevant data was extracted from news articles and posts on social media to determine the sentiment associated (positive/negative/nuetral) along with various other factors. A complex qwantitative measure was designed to gauge the extent to which every news item was likely to impact the various categories of investors.
3. Federated Learning Model: News filtering algorithms were developed and deployed using an FML model which was crafted to train and deploy personalized news filtering algorithms. This caused critical privacy issues in finance to be addressed as sensitive investor data was guaranteed to be kept private and private. The model was trained to detect and understand

news articles that have the highest likelihood of being relevant and impactful to an investor cluster.

4. Personalized News Delivery: The filtered news articles were then presented to investors within their preferred channels. Investors were bewitched and empowered to select what news fit with their investment goals and where it was needed and what decisions would be made

By utilizing FML and incorporating investor behaviour analysis, this work enables the customized communication of financial news while effectively safeguarding privacy. This is this does range wider across geographies. Further work is necessary to develop and polish the system so that its effect and benefits to the Indian investment scene can be felt in full bloom.

6.2 Implications

This research aimed to create a new system of communication addressing the investors need to remain private while empowering them to make better investment in making decisions. This research by using Federated Machine Learning (FML) set out to design a system which aims and prioritizes the personalization of communication through a strong filter of Investment articles based on profiles of the individual investors.

Key Components:

1. Investor Segmentation: The identification process focused on Indian investors was based on multi-dimensional profiling. In this step, various characteristics such as age, gender, risk appetite, medical history, investment horizon, and financial status were evaluated. This analysis made it possible to identify seven clusters of unique investors with distinct preferences and patterns of investing.
2. News Analysis and Sentiment Scoring: The analysis focused on the sentiment of selected news items as well as social media and articles on the internet to determine if they had a positive, negative, or neutral impression. A scoring mechanism was developed, and with it, it became possible to quantify the potential effect each item had on different investor clusters.
3. Federated Learning Model: A Federated Learning Model (FLM) was employed to train and filter personalized news at the micro level, ensuring that each investor's data remained private and not merged with other sensitive data. This remarkable feature of FLM solves the privacy problem in finance. The model was trained to filter out nonessential information, leaving only the most impactful articles for each investor cluster.

4. Personalized News Delivery: The high-impact articles were sent to the respective investors' chosen communication channels. Instead of receiving overwhelming information, investors were able to pick and focus on news topics that matched their investment strategies.

There are several consequences that are significant to note from this research. For instance:

a. Enhanced Investor Decision-Making: This system allows for users to receive tailored informative news articles which in turn helps them to make more educated and effective investing decisions.
b. Improved Financial Literacy: The system can help in improving the financial literacy of the investors by introducing them to market-related issues and increasing their knowledge of how the markets operate.
c. Increased Investor Engagement: The delivery of tailored news may foster investor engagement and participation in the financial markets.
d. Enhanced Data Privacy: The use of FML solves important privacy issues when using the internet, such as privacy preservation through amputation and the possibility of tissue decapsulation during model training.
e. New Opportunities for Financial Institutions: FML enables new personalized services, better client relationships, and insight into client investment decisions and therefore, pivots the research into solid new territory for financial institutions.

6.3 Recommendations for Future Research

This study serves as an excellent starting point for future research on personalized financial news delivery. The following are suggestions for future research:

1. Dynamic Cluster Refinement:
    a. Adaptive Clustering: Formulate the rules for the algorithm in such a way that these algorithms modify investor clusters in real time according to market conditions, investor activity, and personal preferences. In this way, the system will be in tune with the new market conditions and the personal requirements of the individual.
    b. Real-time Cluster Updates: Current system for clustering allots separate labels to metrics based on information obtained from social media, market analysis and volatility to filter and cluster news content.
2. Advanced Sentiment Analysis:
    a. Nuance in Sentiment: Capture the more intricate aspects of investor sentiment such as fear, greed, excitement and uncertainty through sophisticated techniques such as ML based sentiment analysis.
    b. Multi-lingual Sentiment Analysis: Increase sentiment analysis potentials to include social media and news sources from other Indian languages in addition to English.
3. Explainable AI (XAI) for FML:
    a. Transparency and Trust: Create ways to demonstrate and justify a model's decision of cluster or filter news articles to investors which will increase their trust in the model and the firm.

b. User-Friendly Explanations: Phrase model descriptions in simpler terms to make them easily understood by the investors so that they can grasp the knowledge concerning the news received.

4. Integration with Robo-advisors:
    a. Synergistic Solutions: Link the customized news filtering model with robo advisory systems as one device in order to achieve a powerful investment tool.
    b. Automated Portfolio Adjustments: Use the information generated from news articles to automatically readjust the portfolio in accordance with the current market and investor's objectives.
5. Ethical Considerations:
    a. Bias Mitigation: Conduct in-depth research to identify and mitigate potential biases within the news filtering system, such as algorithmic bias or confirmation bias.
    b. User Control and Transparency: Ensure that investors have full control over their news feed and understand the underlying mechanisms of the personalization process.
6. Long-term Impact Assessment:
    a. Behavioural Changes: Conduct long-term studies to assess the long-term impact of personalized news delivery on investor behaviour, risk tolerance, and investment outcomes.
    b. Financial Well-being: Evaluate the impact of the system on investors' overall financial well-being, including their financial literacy, investment satisfaction, and long-term financial goals.

These future research directions build upon the foundation of this research and explore avenues for further innovation and improvement in the field of personalized financial news delivery. By addressing these challenges and exploring these opportunities, researchers can continue to develop more effective and impactful tools for empowering investors in the evolving financial landscape.

Even though FML looks promising these are the future aspects ons security. (Seneviratne, 2024) studies poisoning attacks in Federated Learning (FedML) environments. Here are the key takeaways:

1. Challenges in Evaluating Attacks:
    a. Finding a single, universally applicable metric for evaluating all types of poisoning attacks is difficult.
    b. Traditional metrics like accuracy and loss may not effectively capture the impact of subtle attacks like backdoors.
    c. Qualitative analysis is crucial alongside quantitative metrics.
2. Most Potent Attacks:
    a. Gradient inversion and 100X boost attacks were found to have the most significant negative impact on model performance.
    b. Backdoor attacks were effective in introducing subtle, undetectable backdoors into the trained model.
3. Scalable Attack Simulation:
    a. The researchers developed a scalable framework for simulating poisoning attacks in FedML environments.
    b. This framework can be used with different model types and supports simulations with varying numbers of clients and malicious client proportions.

As it's evident that FML itself may not be sufficiently equipped to tolerate attacks, additional security mechanisms outside FML are needed.

6.4 Conclusion

The work reported in this thesis has proven the concept of developing and implementing a Financial News Delivery System that mobilizes Federated Machine Learning (FML) techniques with a strong focus on investor confidentiality. The study was able to filter news articles related to individual investors by analyzing investor behavior and clustering them into groups before training the model using FML.

An important aspect of their work concerns information evaluation and processing. More specifically, catering the news content to the individual investor increases the effectiveness of investment decisions. In addition, the implementation of FML helps in addressing major privacy issues as a great deal of sensitive investor information is retained in a non physical form.

Nevertheless, this research underlines the manner in which the work is still in-progress. Some of their activities can improve clustering of data, sentiment analysis, generation of explainable AI models, and their integration with other financial technologies like robo-advisors.

To sum-up, achieving the goals set in this project is an important step towards convergence of a more personalized, less impactful, and more privacy protective paradigm of consuming financial news. There is indeed a perfect window of opportunity for addressing the growing complexity of investors' needs with ethics in mind.

APPENDIX A

SURVEY COVER LETTER

Tushar Sood

Tushar3@ssbm.ch

+91-9916459654

15-06-2024

Subject: Invitation to Participate in a Research Survey

Dear [Recipient Name],

My name is Tushar Sood and I am a DBA candidate from SSBM. My research focuses on Behavioural Investments.

This research entails conducting a short survey that collects investors' demographic information in order to filter appropriate news that aims at improving these investors' decision making.

Participation in this survey is completely voluntary. It is also guaranteed that all the information given will be confidential. The survey takes no longer than 10 minutes to complete.

I would appreciate it if you would consider taking part in this research so that behavioural investments can be understood better.Thank you for your time and consideration.

Sincerely,

Tushar Sood

APPENDIX B

INFORMED CONSENT

Tushar Sood

SSBM

Tushar3@ssbm.ch

+91-9916459654

15-06-2024

Thesis Title: Study of Behavioural Finance

You are invited to take part of a study that I, a DBA candidate at SSBM, have designed. The purpose of this study is to analyze investors' demography and to propose a cluster-based filtering of news.

As a participant in this study you will be required to fill out a questionnaire survey and later on a focus group discussion. This research study to which you will be part of is optional. You have the absolute right to withdraw from the study at any time without penalty or consequence. You may also decline to answer any questions that you feel uncomfortable.

By signing below, you acknowledge that you have read and understood the information provided in this consent form and agree to participate in this research study.

Participant Signature: _____

Date: _____

Researcher Signature: _____

Date: _____

APPENDIX C

INTERVIEW GUIDE

The interviews is aimed to delve deeper into the cognitive and emotional factors that influence investment decisions among Indian investors.

1. Interview Objectives:
    a. To understand the motivations, goals, and risk tolerance of Indian investors.
    b. To explore the role of emotions (fear, greed, regret) in investment decision-making.
    c. To identify common behavioral biases observed by investors (e.g., herd mentality, overconfidence, loss aversion).
    d. To understand the sources of investment information and their impact on decision-making.
    e. To explore the role of cultural and social factors in investment behavior.
    f. To gather insights into investor experiences with different investment products and strategies.
2. Interview Guide: A comprehensive interview guide was developed, covering the following key areas:
    a. Demographic Information: Age, gender, occupation, education, marital status, family size, etc.
    b. Investment Experience: Investment history, investment goals (e.g., retirement, wealth accumulation, children's education), investment horizon, risk tolerance.

c. Investment Knowledge and Awareness: Understanding of financial markets, investment products (stocks, bonds, mutual funds, etc.), awareness of financial risks.
d. Investment Decision-Making Process: Information sources, decision-making criteria, role of emotions, influence of family and friends.
e. Experiences with Behavioral Biases: Recognition and impact of common behavioral biases (e.g., herd mentality, loss aversion, overconfidence).
f. Investment Strategies and Approaches: Preferred investment strategies, portfolio diversification, use of financial advisors.
g. Challenges and Opportunities: Challenges faced in investing, opportunities for improvement in the investment landscape.

3. Ethical Considerations:
    a. Informed Consent: Prior to each interview, informed consent was obtained from all participants, ensuring they understood the purpose of the study, the procedures involved, and their rights as participants.
    b. Confidentiality: All participant information was treated with the utmost confidentiality.
    c. Anonymity: Participant names and other identifying information were removed from the data to ensure anonymity.

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