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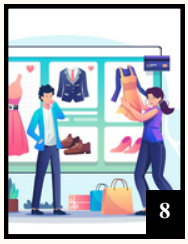
The article investigates dynamic herd behavior in different factor portfolios for the Indian Stock Market.



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DOCTORAL ABSTRACT

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72 Factors Affecting Customer Satisfaction: An Empirical Investigation on Online Banking Services

Mr. Rohit Mahajan

The study discusses how the online banking experience has made everything easy, useful and productive for the customers as well as the institutions, and how satisfied the customers feel about the service they received in general through the model of acceptance of new technologies.

From The Editor's Desk

It is our profound delight to present to our readers, the fortieth issue of DIAS Technology Review.

In modern times 'Sharing economy model' is in-vogue in business corridors. It is a practice of collaborative consumption through community-based online platforms which facilitates sustainable utilization of resources and their monetization, in different sectors of an economy. The resesarch article **"Contributing to the Sharing Economy: A Bibliometric Mapping of Fashion Rental Services"** highlights the potential of such business model in luxury fashion rental services. The authors by a bibliometric analysis have explored the growth trajectory of this model in fashion rental services, which is encountering the risks of inadequate infrastructure, lack of awareness and trust amongst consumers of such services.

In health sector also, the mobile-enabled health technologies are supporting individuals and the public-health agencies in pathological investigations and clinical guidance. The author in **"The study of factors influencing the adoption of mHealth applications among the consumers of Health services"** has used Technology Acceptance Model and Technology Threat Avoidance theory to investigate how users' motivation to avoid perceived threats interacts with their attitudes to shape intentions to adopt mobile-health (mHealth) apps.

The research study **"Herding in Factor Portfolios: A Regime-Switching Perspective on the Indian Market"** pragmatically explores the dynamic herd behavior of different portfolios of Indian Stock Market with respect to factors like large size, high-volume, and value stocks. The author has used Markov model to find out that investors behaviour for various types of stocks relies on the market trends. Similarly, the author of the article **"Volatility in the Banking Sector: A Multivariate Study of FPI and Key Economic Indicators"** has tried to figure out the pattern of cross-border capital movements in integrated global financial markets and their impact on volatility in Indian banking sector. Using a multivariate analytical framework, the researcher has analyzed the interplay between FPI flows and macro variables like interest rates, inflation, and exchange rates that are posing challenge to financial stability.

Human resource, especially Gen Z, strongly believes that their organizational commitment is the outcome of their work-life balance and mental health. In the article **"Organizational Commitment Among Gen Z: The Role of Job Security, Development, and Well-being"** the author has examined the influence of job security, training and development opportunities, compensation practices, and employee mental well-being on organizational commitment among Generation Z professionals in the Delhi NCR region. This study results align with the Job Demands-Resources (JD-R) model and thus, help organizations to design evidence-based HR strategies.

The doctoral **abstract "Factors Affecting Customer Satisfaction: An Empirical Investigation of Online Banking Services"** proposes and tests "TAM" model to account for numerous aspects influencing individual acceptance, perceived utility and easiness & perceived risk usage of online bank service at India.

In our mission of acquisition and proliferation of knowledge in different areas of business and IT, we expect that the present edition of this journal with all its illuminating features will come upto the expectations of our revered readers.

Regards,

Dr. Anju Batra

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Contributing to the Sharing Economy: A Bibliometric Mapping of Fashion Rental Services

*Ms. Ronika Bhalla, **Prof. Meenakshi Handa, ***Dr. Amit Sharma

ABSTRACT

Along with other constituents of the sharing economy, fashion sharing services have the potential to make valuable contributions towards sustainable consumption and production. However, there is a dearth of studies on the linkages amongst the prominent research units of analysis and development of scholarship on fashion rental services. This study aims to map the evolution and structure of the discourse on fashion rental services through bibliometric analysis and to identify the major challenges impeding the growth of fashion rental services. A total of 133 papers have been analyzed through Biblioshiny and VOS viewer software to identify the prominent contributors including authors, journals, institutions, and countries. Co-citation analysis, author collaboration network, and keyword co-occurrence analysis have been undertaken. Thematic mapping indicates collaborative fashion consumption and fashion as motor themes and sharing economy and clothing as basic themes. Sustainable consumption and sustainable fashion are emerging themes and luxury fashion and fashion leadership are niche themes. A content analyis of the top highly cited papers in the domain indicate a lack of awareness and trust amongst consumers, perceived risks, and inadequate infrastructure as challenges impeding the growth of fashion rental services. The study lays down a roadmap for future research on fashion rental services and outlines a set of recommendations for stakeholders.

KEYWORDS

Sharing economy, Fashion rental services, Collaborative consumption, Bibliometric analysis

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INTRODUCTION

The production of textiles emits 1.2 billion tons of greenhouse gas while three out of every five clothes produced are thrown into landfill every year (McKinsey & Company, 2023). Fast fashion purchases are increasing but these items are used fewer number of times (Amasawa et al., 2023) and discarded improperly (Zamani et al., 2017). Some consumers are concerned about the economic, social and environmental impact of their consumption including issues such as climate change (Deloitte, 2024; Hamari et al., 2016). They are attempting to reduce the ecological impact of their consumption by purchasing goods or services based on the environmental effect and are even spending more to buy eco-friendly offerings (Deloitte, 2024). Others are refraining from fast fashion and air travel, adopting a vegan diet, and buying e-vehicles (Deloitte, 2024). Some consumers are being attracted towards the sharing economy (Hamari et al., 2016).

The sharing economy is of substantial economic and practical significance to the environment, consumers, and society (Belk, 2014). People looking for sustainable consumption activities are of the view that collaborative consumption is a component of sustainable development (Jain & Mishra, 2020). Collaborative consumption encourages the efficient usage of scarce resources by offering the opportunity to share them amongst consumers thereby eliminating the need for ownership, curtailing the production of assets (Palgan et al., 2017), and contributing to sustainable consumption and production (Boar et al., 2020). Also, it lessens the emission of harmful gases and waste, generates business and employment opportunities for people, and improves their living standards (Boar et al., 2020).

Schor (2014) classifies activities under the sharing economy into four types: recirculation of assets, enhanced use of durable goods, service exchange, and sharing of useful assets. The collaborative consumption of fashion products involves the recirculation of fashion offerings (Camacho-Otero et al., 2019). The growth of firms such as Rent the Runway and Poshmark indicates the participation in the sharing economy by the fashion sector (Jain & Mishra, 2020). The sharing economy encompasses renting clothes, purchasing second-hand clothing, peer-to-peer lending, clothing libraries, and swapping to extend the service life of clothes (Amasawa et al., 2023; Becker-Leifhold & Iran, 2018; Westerberg & Martinez, 2023). The growing environmental concern of consumers is also increasing their proclivity towards sustainable fashion choices including fashion sharing (Forbes, 2024). Some major fashion rental service providers reported a substantial surge in their revenues in 2023 (Forbes, 2024) and the global earnings of the apparel rental market are anticipated to rise to around USD 7.5 billion by 2026 (Statista Research Department, 2024). From USD 2,604.9 million in 2025, the online clothing rental segment worldwide is expected to increase by a CAGR of 9.5 % to USD 6,388.8 million by the year 2035 (Future Market Insights, 2025). The demand for online clothing rentals service is anticipated to rise more amongst males than females from 2022 to 2032 (Allied Market Research, 2023). Also, the segment of luxury fashion rentals is likely to grow by a CAGR of 11% during the decade ending 2031 (Indian Express, 2025).

Fashion rental services are, however, still at a nascent stage in some regions of the world such as Africa, the Middle East, Latin America, and some Asian countries (Allied Market Research, 2023). Amongst the various segments of the sharing economy, there is limited research exploring the area of fashion sharing (Laudien et al., 2023). The present study aims at mapping and synthesizing the current state of understanding of the various constituents of the fashion rental services market. The study findings will inform on the performance and patterns amongst leading research contributors in the literature on fashion rental services. Further, the conceptual trends and themes in the extant research on the fashion rental services will indicate the current state of knowledge in the field and will be instrumental in drawing up directions for future research. The study will also provide an outline of obstacles impeding the development of fashion rental services thereby offering avenues for further research that can make significant contributions to the discourse on the subject. The insights drawn from the study form the basis of a set of recommendations for fashion rental businesses to support them in their endeavours to promote and sustain their services. The study also contributes to developing strategies that encourage consumers to make environment-friendly and affordable choices from a wide range of fashion products, including high-end options, without owning them (Lang et al., 2020; Laudien et al., 2023). Fashion rental services diminish the adverse consequences of consumption on the environment by increasing the usage frequency of fashion offerings (Amasawa et al., 2023) and reducing the production of new products thereby reducing resource consumption and consequent carbon emissions (Lang et al., 2020). Fashion rental services contribute towards the growth of the circular economy and a more sustainable planet. The suggestions will also help government and policymakers in devising appropriate strategies supporting sustainability in the fashion sector.

In the context of fashion rental services, studies have examined the drivers impacting consumer adoption of services (Jain & Mishra, 2020; Lang et al., 2019; Lang & Armstrong, 2018a) and their influence on the environment (Iran & Schrader, 2017; Johnson & Plepys, 2021; Zamani et al., 2017). Some studies have conceptually reviewed the existing literature on collaborative fashion consumption (Becker-Leifhold & Iran, 2018; Park & Armstrong, 2017). However, the research examining the linkages amongst the prominent research units of analysis and development of scholarship on fashion rental services remains limited. This study aims to bridge this gap by answering the following

research questions:

RQ1: How have the publications on fashion rental services evolved?

RQ2: Which are the leading contributors including authors, publications, journals, institutions, countries, and references in the literature on fashion rental services?

RQ3: What are the prominent themes in the research on fashion rental services?

RQ4: What are the challenges facing the development of fashion rental services?

RQ5: What are the future research avenues in the present domain of study?

For achieving its purpose, the present study employs bibliometric analysis and content analysis. Bibliometric analysis evaluates and outlines the intellectual, social, and conceptual structure of the research domain by examining the performance of and relationships amongst different units of analysis such as documents, authors, and countries (Donthu et al., 2021). Performance mapping refers to the assessment of performance of units of analysis such as most impactful publications and authors to determine their contributions to the research domain (Donthu et al., 2021; Zupic & Cater, 2015). Science mapping refers to the examination of relationships between units of analysis such as co-citation analysis and keyword co-occurrence analysis to present the structure and evolution of research domain (Donthu et al., 2021; Zupic & Cater, 2015). Content analysis is employed to understand latent concepts and constructs by drawing inferences from the qualitative secondary data for further analysis (Gaur & Kumar, 2018). It is a cost-effective, non-invasive and analytically flexible approach (Duriau et al., 2007).

2. LITERATURE REVIEW

Consumers are considering fashion rental services more than other types of collaborative fashion consumption (Lang et al., 2019). Some well-known examples of fashion rentals are Rent the Runway, Gwynnie, Le Tote, and HURR (Lang & Zhang, 2024). The foundation of fashion rental services is based on the idea of access over ownership so it lacks the burden of owning a product (Lang et al., 2019). The firm owns the product and offers its access to consumers through an online platform or physical store for a fee for a certain period (Camacho-Otero et al., 2019). The repair, maintenance, and control over the product remains with the service provider firm whilst the consumer gets the usage rights for the fee (Becker-Leifhold, 2018). Further, Lang et al. (2019) state that internet and technological developments can make collaborative fashion consumption easily accessible to many consumers worldwide thus enabling their participation in these services. Chi et al. (2023) posit that fashion rental services should be made simpler and more convenient to use for consumers to be confident about their usage of services to make them more effective.

Several factors drive consumers' usage of fashion rental services. Becker-Leifhold & Iran (2018) indicate that consumers with limited money or wanting to minimize expenditure on occasional fashion goods and are frugal or seeking bargains prefer using fashion rental services (Lang & Zhang, 2024; Myin et al., 2023; Park & Armstrong, 2019). For some, the feeling of fun and excitement from enjoying the use of fashion products drives them towards these services (Lang et al., 2019; Ruan et al., 2022; Tao & Xu, 2020). Fashion rentals enable individuals to update their wardrobe regularly with trending fashion and multiple styles without owning new clothes while saving space (Noe & Hyun, 2024; Park & Armstrong, 2019; Westerberg & Martinez, 2023). Jain & Mishra (2020) and Mishra et al. (2021) posit the opportunity for social projection and past sustainable behaviour as predictors of consumption of luxury fashion rentals. Perceived ease of use, style-related benefits (Pham et al., 2021; Tao & Xu, 2020), and reduced time involved in product return and refund (Park & Armstrong, 2019) are some other consumer motivations towards fashion rental services. Sustainability is another important driver towards the renting of everyday clothes (Bodenheimer et al., 2022; Ruan et al., 2022; Westerberg & Martinez, 2023).

Westerberg & Martinez (2023) posit that fashion rentals are reshaping the fashion sector to form a circular fashion sector thus leading to sustainability. The sharing of fashion is a part of the circular business model as it provides consumers with access to trending fashion and luxury items without owning them (Lang & Zhang, 2024). This way less fashion products will be manufactured and the existing ones will be optimally utilised before disposal (Amasawa et al., 2023; Iran & Schrader, 2017). Chi et al. (2023) state that by reducing clothing waste and encouraging the reuse of clothes, the carbon footprint of the fashion sector can be decreased. Iran & Schrader (2017) posit that collaborative fashion consumption increases the service life of clothes by increasing their use frequency through renting out. This helps to diminish the adverse impact of fashion rental services on the environment (Monticelli & Costamagna, 2023). It helps in lowering excess consumption and reduces adverse effects on the environment (Lang et al., 2019). Amasawa et al. (2023) posit that clothes having high fabric content and embodied carbon of fibers produce less greenhouse gases. Also, extending the lifetime wear of garments decreases the generation of these harmful gases.

3. METHODOLOGY

This study is based on bibliometric analysis conducted on documents collated according to PRISMA guidelines (Moher et al., 2009) (Figure 1) and further processed using the Biblioshiny tool of Bibliometrix R-package and VOS view-

er. On 24 September 2024, an advanced search was undertaken using the following search query in Scopus and Web of Science (WoS) for publications having the following words in their title and author keywords without a period filter:

((“collaborative consumption” OR “sharing economy” OR “peer to peer”) AND (“cloth*” OR “fashion” OR “apparel*”)) OR ((“fashion” OR “cloth*” OR “apparel”) AND (“rent*” OR “subscription’ OR “share*”)) OR (“collaborative fashion consumption”))

The records were restricted to include journal articles including early access and review papers in the English language only. This led to the listing of 299 publications from which 114 were identified as duplicates and were removed. Further, a manual screening as suggested by Lim et al. (2024) resulted in the removal of 2 publications. The scrutiny of the remaining 183 papers informed that 50 publications were not related to the area of interest. Thus, 133 papers were finally included in the bibliometric analysis.

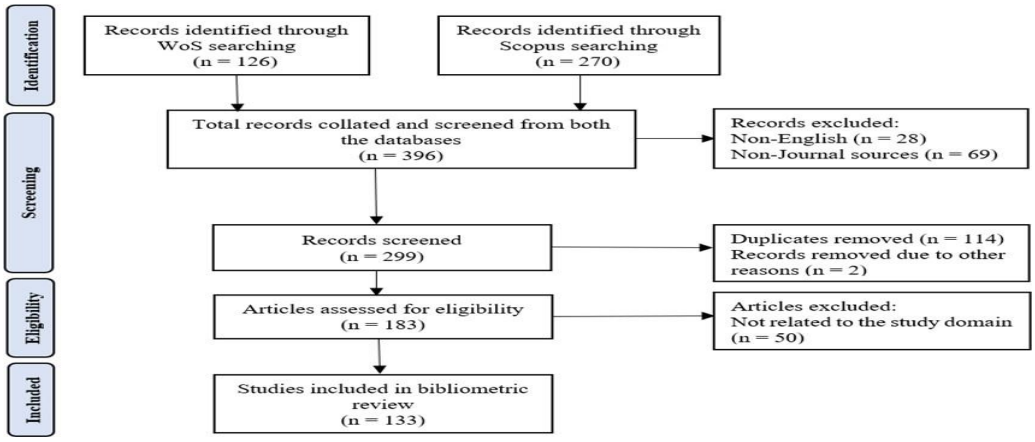

Figure 1. Review Protocol Adapted From PRISMA Flow Diagram

This study uses the Biblioshiny tool and VoS viewer to perform bibliometric analysis (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010). Biblioshiny informs on the trends pertaining to the thematic development and VoS viewer provides understanding on the state of evolution of topic in the study field (Lim et al., 2024). Prior studies have also employed both the software to conduct bibliometric analysis (Bamel et al., 2022; Bretas & Alon, 2021; Niknejad et al., 2021). Further, a content analysis of 20 studies that have the highest total global citations was performed to identify the challenges impeding the growth of fashion rental services.

4. RESULTS

The presentation of the results of the bibliometric analysis begins with a description of publications’ trend followed by the most impactful contributors, author collaboration network, keyword co-occurrence analysis, and conceptual thematic mapping of studies on the fashion rental services.

4.1. Annual Publications and Citations

The present section indicates the annual output and the sum of citations per year of publications on fashion rental services (Figure 2). The first publication in this area is from Pedersen & Netter (2015). Subsequently, the publications continued to grow and reached the highest count in 2023 (25). The sum of citations was 128 in 2015, followed by a trend of downswings and upswings reaching a maximum at 773.95 in 2021.

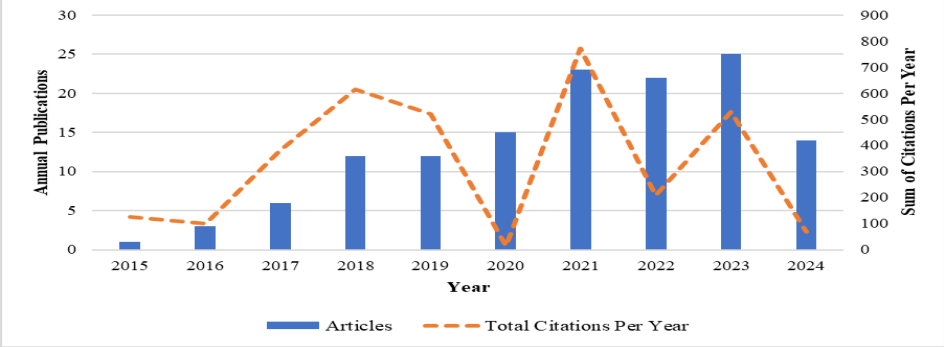

Figure 2. Trend Of Publications And Citations

4.2 Most Impactful Contributors

Table 1 presents the ten highly cited papers in the order of their local citations. It also indicates their impact based on local citations per year, global citations, and global citations per year. Global citations determine the number of citations that a publication receives from the whole database including other disciplines, whereas local citations consider the number of citations that a publication receives from the papers forming a part of the data under analysis (Agbo et al., 2021). Lang & Armstrong (2018a) is the most impacted publication in terms of local citations investigating the impact of personality traits on consumers' adoption intention towards collaborative consumption through renting of clothes. Zamani et al. (2017), having the highest global citations, examine the impact of clothing libraries on the environment.

Table 1. Ten Highly Cited Publications

Author(s) & Year	Local Citations (LC)	LC Per Year	Global Citations (GC)	GC Per Year
Lang & Armstrong (2018)	27	3.86	142	20.29
Iran & Schrader (2017)	25	3.13	88	11
Park & Armstrong (2017)	20	2.5	80	10
Becker-Leifhold & Iran (2018)	20	2.86	87	12.43
Johnson (2016)	19	2.11	52	5.78
Lee & Chow (2020)	19	3.8	97	19.4
Lang et al. (2020)	17	3.4	43	8.6
Zamani et al. (2017)	16	2	150	18.75
Becker-Leifhold (2018)	16	2.29	87	12.43
Lang et al. (2019)	16	2.67	40	6.67

The top ten most impactful authors contributing to the literature on fashion rental services are listed in Table 2. h_index denotes that h number of research papers have at least h number of citations (Hirsch, 2005). g_index suggests that g number of most cited papers have at least g2 citations and m_index indicates h_index per number of years since the date of first research paper published (Dhiaf et al., 2021). Chunmin Lang has maximum papers, citations, h_index, g_index, and m_index.

Table 2. Most Impactful Authors

Author	Publication Count	Year of First Publication	Total Citations	h_index	g_index	m_index
Chunmin Lang	8	2016	359	6	8	0.667
Hyejune Park	6	2017	182	4	6	0.5
Cosette Marie Joyner Armstrong	5	2016	350	5	5	0.556
Claudia E. Henninger	5	2019	130	4	5	0.667
Samira Iran	4	2017	264	4	4	0.5
Stacy H. Lee	4	2020	183	4	4	0.8
Ting Chi	4	2021	44	3	4	0.75
Sheetal Jain	4	2020	111	3	4	0.6
Sita Mishra	3	2020	109	3	3	0.6
Yingjiao Xu	3	2018	41	3	3	0.429

Table 3 presents the most relevant journals, author-affiliated institutions, and countries along with their number of publications. Sustainability has the highest number of publications, followed by the Journal of Fashion Marketing and Management and the Journal of Cleaner Production. A significant contribution to the literature on fashion rental services has been made by the universities based in the USA. A large number of studies are from developed countries such as the USA, the UK, Germany, Italy, and South Korea.

Table 3. Most Relevant Journals, Author-Affiliated Institutions, And Countries

Sources	Articles	Affiliation	Articles	Country	Articles
Sustainability	23	Louisiana State University	9	USA	39
Journal of Fashion Marketing and Management	15	Louisiana State University System	7	China	12
Journal of Cleaner Production	9	North Carolina State University	7	United Kingdom	12
International Journal of Fashion Design, Technology and Education	6	Oklahoma State University System	6	Germany	8
Journal of Retailing and Consumer Services	5	Hong Kong Polytechnic University	5	India	8
Transportation Research Part E-Logistics and Transportation Review	4	University of Minnesota System	4	Spain	4
Business Strategy and The Environment	3	University of Minnesota Twin Cities	4	Sweden	4
Fashion and Textiles	3	University of North Carolina	4	Belgium	3

4.3. Co-citation Analysis

Co-citation analysis intellectually examines the research subject depending on the frequency of occurrence of two papers together in another paper (Donthu et al., 2021). Each cluster points towards a research theme based on the relation between the content of cited papers (Zupic & Cater, 2015). A network of 38 cited references out of 6,855 references from 133 papers each having at least 10 citations is indicated in Figure 3. Cluster 1 (12 papers) examines the motivators and deterrents to the consumers' adoption of fashion rental services (Becker-Leifhold & Iran, 2018; Lee & Chow, 2020). Cluster 2 (11 papers) mainly focuses on consumer behaviour towards collaborative consumption in the context of various services (Bardhi & Eckhardt, 2012; Möhlmann, 2015). Cluster 3 (10 papers) primarily pertains to product-service systems and fashion libraries (Tukker, 2004; Zamani et al., 2017). Armstrong et al. (2015) is the most significant study in the network based on citation count and total link strength. It investigates the perceptions of consumers about product-service systems for clothing.

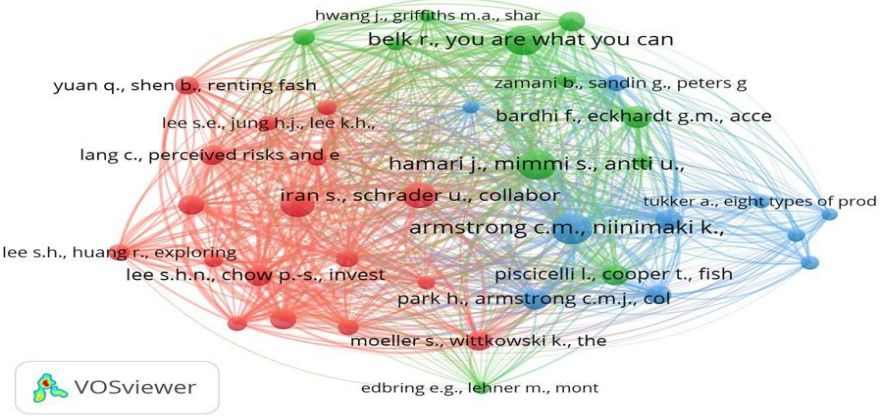

Figure 3. Co-Citation Map Of Papers

4.4. Co-authorship Network

Co-authorship network determines the collaboration amongst authors authoring a research paper and presents the social network in the research area (Zupic & Cater, 2015). The network depicting the social structure in the area of fashion rental services amongst 30 authors is indicated in Figure 4 through Biblioshiny. Cluster 1 has four authors (Lang, C.; Armstrong, C. M. J.; Park, H.; Liu, C.) who have examined the factors driving consumers' participation in collaborative consumption of and product service systems for clothes.

Cluster 2 consists of four authors (Mishra, S.; Jain, S.; Jain, K.; Jain, R.) who have mostly investigated the drivers of fashion rental services in the Indian context. Cluster 3 has four authors (Becker-Leifhold, C.; Iran, S.; Brydges, T.; Henninger, C.) who have systematically reviewed the literature on collaborative fashion consumption. Cluster 4 encompasses two authors (Lee, S.; Huang, R.) whose papers have focused on consumer behaviour towards online fashion renting. Cluster 5 has two authors (McCoy, L.; Chi, T.) who have analysed collaborative consumption of apparel from the perspective of sustainability. Cluster 6 has two authors (Kim, N.; Jin, B.) whose publications pertain to the contamination aspect of collaborative fashion consumption.

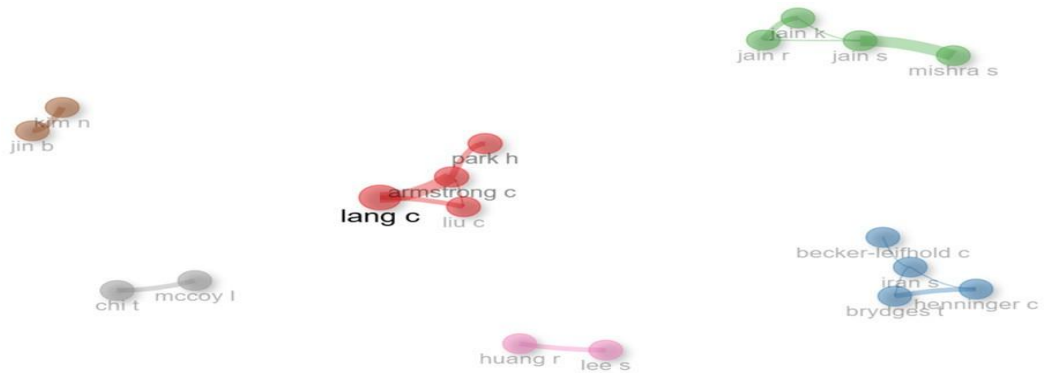

Figure 4. Co-Authorship Map Of Authors

4.5. Key Countries, Authors, and Keywords

The associations amongst countries (left), authors (center), and author keywords (right) in the research on fashion rental services have been indicated in Figure 5. Around 9 out of 20 authors (Lang, Park, Chi, Armstrong, Lee, Wang, Xu, Lee, Huang) are from the USA whose proficiency pertains to 'collaborative consumption', 'fashion renting', 'sharing economy', 'sustainability', 'collaborative fashion consumption', 'attitude', 'fashion renting', 'fashion leadership', and 'access-based consumption'. Amongst the keywords, 'collaborative consumption' (13 links) and 'sharing economy' (13 links) have been used the highest number of times, followed by 'sustainability' (8 links) and 'swapping' (6 links) in the literature on fashion rental services.

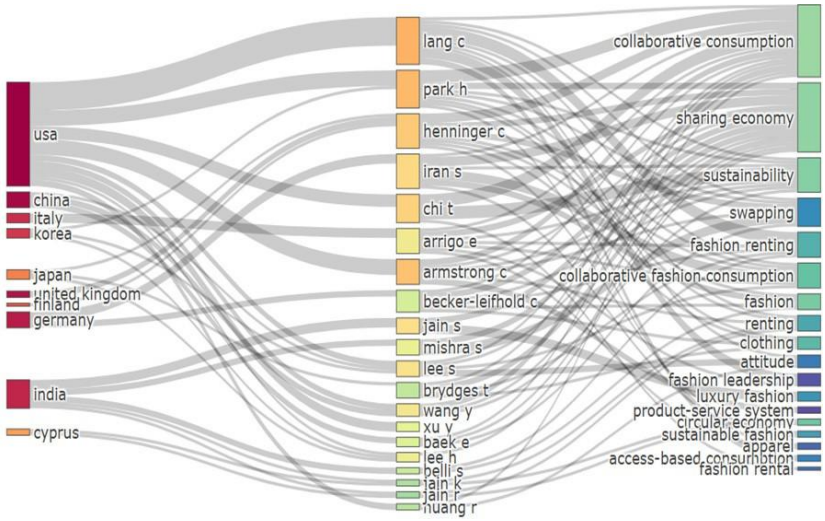

Figure 5. Key Countries, Authors, And Keywords

4.6. Keyword Co-occurrence Analysis

Keyword co-occurrence analysis presents thematic associations amongst terms frequently co-occurring in the network (Donthu et al., 2021). Figure 6 indicates three clusters formed through 17 author keywords out of 416 keywords appearing at least six times. Cluster 1 has seven terms such as 'circular economy', 'collaborative fashion consumption', 'product-service system', and 'clothing rental services' and mostly relates to the drivers of and barriers to the adoption of collaborative fashion consumption.

Cluster 2 includes five terms such as 'collaborative consumption', 'luxury fashion', and 'renting' and focuses on collaborative consumption towards fashion products including swapping, renting, and consumption of second-hand clothing. Cluster 3 consists of five terms, namely, 'sharing economy', 'fashion rental services', and 'sustainability'. It pertains to fashion rental services from the perspective of sustainability. 'Sharing economy' has the highest number of occurrences (37) and the number of links (15) and the strongest link with 'collaborative consumption' that has the second highest occurrences (53) and the highest total link strength (53).

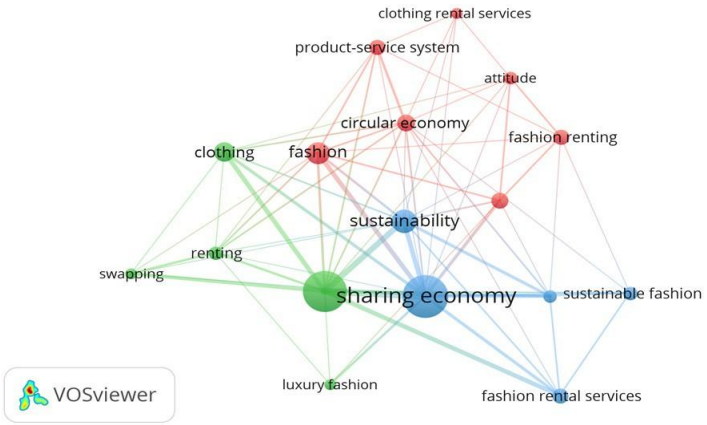

Figure 6. Keyword Co-Occurrence Map

4.7. Conceptual Thematic Map

A conceptual thematic map indicates themes in a research area formed according to the relationships amongst keywords and plotted based on their centrality (importance) and density (development) (Callon et al., 1991; Cobo et al., 2011). Figure 7 presents eight clusters identified in the literature on fashion rental services based on author keywords and developed using Biblioshiny.

'Collaborative fashion consumption' and 'fashion' are the two motor themes. This suggests that collaborative consumption of fashion products is the essence of fashion rental services. It includes systematic examinations of studies on collaborative fashion consumption (Henninger et al., 2021) and the motivators of (Khitous et al., 2022) and barriers to the use of product-service systems in the fashion sector (Lang, 2018; Lang et al., 2019). The papers related to 'fashion' investigate the practice of clothes' renting through practice theory (Ulrich et al., 2024), the adoption of collaborative fashion consumption in renting mode (Jain et al., 2022) and luxury fashion products of second-hand nature (Kim-Vick & Cho, 2024), and the consumer perceptions of fashion rental firm - Rent the Runway (McKinney & Shin, 2016).

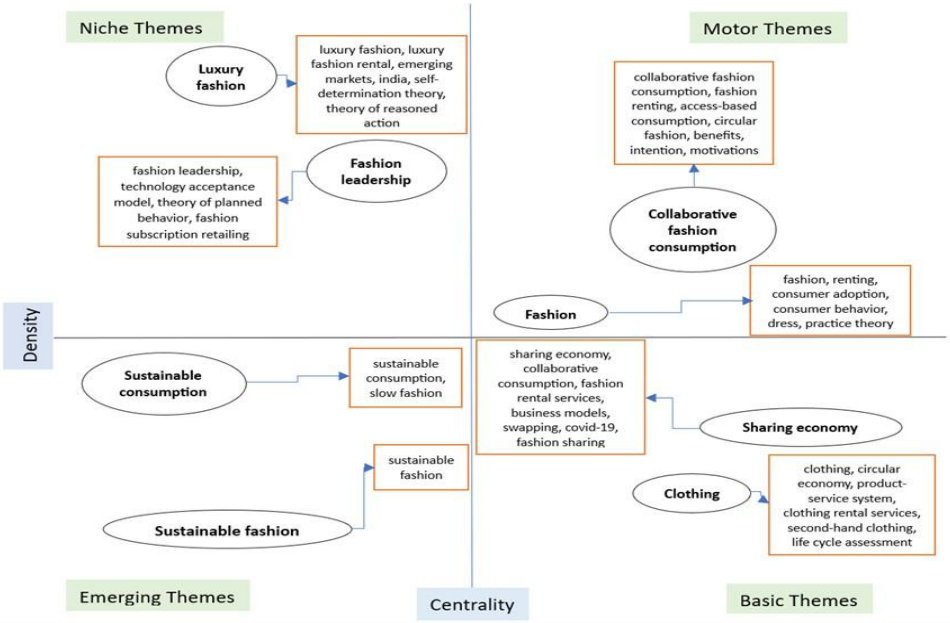

Figure 7. Conceptual Thematic Map

Of the two basic themes, 'sharing economy' is the largest theme involving the examination of business models related to fashion rentals (Holtström et al., 2019), swapping (Henninger et al., 2021), influence of fashion rentals on sustainability (Amasawa et al., 2023), drivers of consumer behaviour towards online renting (Lee & Chow, 2020), and the impact of Covid-19 on fashion renting services (Park & Lee, 2022). 'Clothing' is based on the environmental impact of clothing renting (Johnson & Plepys, 2021; Monticelli & Costamagna, 2023) and antecedents to the sharing of second-hand clothing (Camacho-Otero et al., 2019; Xu et al., 2014).

Amongst the two niche themes, 'fashion leadership' examines the role of fashion leadership towards product-service systems for clothing (Lang & Armstrong, 2018b), the intention to adopt fashion subscription retailing services (Tao & Xu, 2020), and online fashion rentals based on the theory of planned behaviour and technology acceptance model (Pham et al., 2021). 'Luxury fashion' identifies the determinants of luxury fashion consumption in the sharing economy and collaborative consumption on a rental basis through the application of the theory of reasoned action and self-determination theory in the emerging economies of India (Jain & Mishra, 2020) and UAE (Mishra et al., 2021).

Of the two emerging themes, having relevant papers published recently, 'Sustainable fashion' addresses issues about sustainable fashion through renting (Palomo-Domínguez et al., 2023; Savelli et al., 2024). 'Sustainable consumption' emphasizes sharing of clothes as a means to slow fashion (Costa et al., 2024).

5. CHALLENGES FACING FASHION RENT AL SERVICES

Various challenges impeding the growth of the business model of fashion rental services have been identified through a content analysis of the top 20 publications based on the highest global citations.

Despite garnering interest in some quarters, the market for fashion rental services is still in a nascent stage. Many consumers are not familiar with how this business model operates (Becker-Leifhold & Iran, 2018; Jain & Mishra, 2020; Lang & Armstrong, 2018a; Shrivastava et al., 2021). Often, they lack the knowledge about where to obtain clothes on rent and therefore are not able to partake of the fashion rental services (Becker-Leifhold, 2018). Some consumers believe that they require much time to search for such rented products (Iran et al, 2019). Consumers lack awareness about the guarantees offered by the services (Becker-Leifhold & Iran, 2018). They also have concerns about penalties that they would be charged for treatment of damages by fashion rental services (Becker-Leifhold & Iran, 2018).

Some consumers lack trust in fashion rental products, the service providers, and their services (Becker-Leifhold & Iran, 2018). Not only are rented fashion products available for use for a limited time but their offerings are second-hand in nature (Iran & Schrader, 2017). Consumers perceive certain risks related to the usage of fashion rental services. These pertain, in the main, to performance risk, physical risk, financial risk, and psychological risk. These perceived risks adversely impact their attitude towards and enjoyment of rented fashion products (Lang, 2018). Some consumers do not find the expenditures on fashion rental services worth the while for a short span of time and consider them to be a waste of money (Lang, 2018). Consumers are bothered about maintaining the rented products in good condition and the consequences to be borne by them in case of poor maintenance or damages (Lang, 2018). Uncertainty about whether the rented fashion products would suit them and doubts about delivery of services commensurate with the price paid influence perceptions towards fashion rentals (Lang, 2018). Thus, the reputation of the fashion rental service provider and the duration for which the provider has been running the business are some of the concerns of consumers related to fashion rental services (Becker-Leifhold & Iran, 2018). Concerns about the hygiene aspects of rented fashion products such as clothing persist as these items are worn by other consumers close to their skin and there are apprehensions that, if not clean, they may transmit diseases (Becker-Leifhold & Iran, 2018; Lang, 2018). Some consumers view these clothes as quite repulsive (Iran et al., 2019). Further, there is some perceived social stigma associated with the consumption of second-hand clothes (Shrivastava et al., 2021). The stigma could be due to cultural norms adversely influencing consumer attitude towards collaborative fashion consumption, for instance, the consumption of second-hand apparel denotes low economic status in Tehran (Iran et al., 2019). Consumers may not enjoy renting fashion products if they perceive that doing so diminishes their self-image, status, and personal style (Lang, 2018). Persuading individuals to share apparel with other individuals who are strangers needs a significant transformation in their behavioural patterns (Jain & Mishra, 2020). Lack of personal ownership of fashion apparel and difficulty in changing consumption habits to a new mode of consumption hinder sharing amongst consumers (Becker-Leifhold & Iran, 2018).

Research indicates that some individual personality traits have a bearing on consumer behaviour with regard to participation in fashion rental services. A negative relationship has been suggested between materialism, that is, the desire to have more material possessions (Lang & Armstrong, 2018a) and purchase of fashion rental services. Whereas fashion rentals promote the concept of sharing over owning, materialistic consumers strive to increase their material possessions and avoid sharing apparel with others (Johnson et al., 2016; Lang & Armstrong, 2018a), as likely this may not provide them the same gratification.

Fashion rental service providers also face certain challenges.

Amongst these is the need to create primary demand for the service concept (Becker-Leifhold & Iran, 2018). Service providers need to clearly communicate their value proposition and to be able to resist competition from various inexpensive fashion products (Becker-Leifhold & Iran, 2018). Many products are used once or twice so the challenge to increase their frequency of use continues to exist (Iran & Schrader, 2017). They also need to deal with the problems of inadequate infrastructure and reverse logistics supply chain (Becker-Leifhold & Iran, 2018). The lack of proper regulations impedes the growth of fashion rentals (Shrivastava et al., 2021).

6. FUTURE RESEARCH DIRECTIONS AND MANAGERIAL IMPLICATIONS

The study findings indicate several areas pertaining to fashion rental services that need further examination. Empirical research is required to further investigate the transition in consumer behaviour from owning to renting clothes (Amasawa et al., 2023). Experimental studies can be conducted to examine consumer responses to the strategies promoting collaborative fashion consumption (Becker-Leifhold, 2018). A mixed-method approach examining consumers' online reviews in combination with methods such as ethnography, focus groups, and interviews can be undertaken for a deeper understanding of consumer experiences with fashion rental services (Camacho-Otero et al., 2019).

The impact of consumer values on the use intention of consumers towards collaborative fashion consumption can be examined across demographics and cultural aspects (Becker-Leifhold, 2018). Cultural factors, psychosocial factors, and personality traits as antecedents of consumer adoption intention can be investigated (Camacho-Otero et al., 2019). Future research can examine the relationship between particular occasions and consumer participation in collaborative fashion consumption (Lee & Chow, 2020). There is limited research examining service quality, customer satisfaction, and continuance usage intention in the context of fashion rental services. The attitudes and continuance behaviour of consumers towards fashion rental services can be investigated through longitudinal research (Lang & Armstrong, 2018a). Consumer perception towards fashion rental services can be examined across generational cohorts such as baby boomers vs. Generation Z.

The motivators and barriers influencing consumer behaviour towards fashion rental services can be compared for users and non-users (Lang et al., 2019) and amongst consumers in developing (Ulrich et al., 2024) and developed economies. Consumer perception towards fashion rental services can be examined based on the mode of access, that is, online vs. physical stores. Factors leading to consumer usage of fashion rental services can be contrasted based on the service provider such as Rent the Runway and Gwynnie, type of fashion product such as clothing, handbag, and shoes, type of clothing such as office wear, wedding wear, and sportswear. Consumer interaction with various types of garments such as designer labels and fashion forward pieces needs to be studied (Amasawa et al., 2023). Future studies can examine the rebound impact of consumption through fashion rental services on the purchase of other fashion products such as handbags and shoes (Johnson & Plepys, 2021). Future research can explore fashion rental consumption from the perspective of service providers.

The impact of the fashion rental services on the economy in general and its contribution to the circular economy in particular needs further study. Fashion rental services have created a new business model, generating job opportunities, new streams of revenues for fashion brands, need for technology integration, requirement for innovations in inventory and supply chain management and service design. At the same time, these services lead to resource efficiency and reduce production of fashion products. As this new business model evolves, its net impact on the economy needs to be studied. The contribution of the fashion sharing services towards the attainment of sustainable development goals can be explored. More empirical evidence on various aspects of fashion sharing from the perspective of sustainable consumption is required. The impact of the type of garments and product design offered through fashion rental services on environmental sustainability can be explored (Amasawa et al., 2023). Also, research can be conducted to examine various forms of fashion sharing such as P2P and B2C. Future studies can compare the contributions of fashion rental services with other sharing economy services such as ride sharing and accommodation sharing services towards the development of sharing economy. Also, a contrast can be drawn on the drivers of fashion sharing with other types of sharing services from the perspective of consumers, service providers, and platform operators using mixed methodology.

Lack of awareness and trust amongst consumers, perceived risks, lack of ownership, and inadequate infrastructure and regulations are identified as some of the challenges being encountered by fashion rental services. The role of trust in influencing the usage intention towards fashion rental services needs further understanding. Further studies can explore the factors impacting the formation of consumer trust towards service providers and platforms while considering various risks such as performance risk and psychological risk. Strategies to boost the idea of collaborative fashion consumption amongst consumers and overcome hindrances can be investigated (Becker-Leifhold & Iran, 2018). Interventions to persuade materialistic consumers' participation in fashion rental services can be examined using qualitative techniques.

The benefits of fashion sharing need to be clearly communicated to consumers through appropriate strategies. Fashion

rental services can be promoted through online channels including social media influencers particularly focusing on fashion, lifestyle, and sustainability. The value proposition of fashion rental services should be clearly conveyed to consumers by emphasizing their benefits such as more and diverse variety, freedom from the responsibility of ownership and repair using an "ownership-like" mode of consumption (Jain & Mishra, 2020), hedonistic experiences, and sustainability (Lang & Armstrong, 2018a). Consumer concerns can be dealt with by providing assurances about quality and hygiene and clear policy guidelines informing consumers about the functioning of the fashion rental service business model, guarantees, maintenance requirements, and damage-related obligations. Brand reputation will be an important factor in building consumer trust as it helps in assuaging their concerns and risk perceptions towards this new form of consumption.

7. CONCLUSION

Adding to previous studies involving systematic literature reviews (Becker-Leifhold & Iran, 2018; Henninger et al., 2021) and empirical examinations (Bodenheimer et al., 2022; Jain & Mishra, 2020) in the context of fashion sharing, the present study maps the evolution and structure of the discourse on fashion rental services through bibliometric analysis and highlights new directions for future studies in this domain. This study provides a holistic view of the structure of the current state of research on fashion rental services including intellectual structure, social structure, and conceptual structure depicting the relationships between research constituents and trends pertaining to the topic development. The study also identifies and underscores the challenges hindering the growth of these fashion rental services. It identifies eight themes prominent in the studies on fashion sharing. Collaborative fashion consumption and fashion are developed themes that are significant in the literature on fashion rental services and are strongly linked to other themes as well. The sharing economy and clothing are not well developed yet very important to the present domain of research. Sustainable consumption and sustainable fashion are emerging themes that are little developed and can gain importance in the future through further examination. Fashion leadership and luxury fashion are niche themes of a peripheral nature that are already developed but weakly related to other topics. The present analysis thus highlights that a high proportion of extant research is focused on collaborative fashion consumption and fashion. There is thus a need for enhancing the understanding in the domain by also focusing on the emerging areas of sustainable consumption and sustainable fashion. Further research is needed on the development of appropriate interventions to address challenges such as lack of awareness and consumer trust, perceived risk, lack of ownership, and inadequate infrastructure and regulations, amongst others.

Further, the implementation of suggested recommendations will encourage the growth of fashion sharing and its contribution to the overall sharing economy. Awareness generation through effective communication, emphasis on value proposition, and implementation of necessary protocols and guidelines to manage consumer risks will lead to the growth of fashion sharing businesses and enhance their role in the sharing economy. It will also give impetus to the discourse in the public domain on emerging topics in relation to fashion sharing such as sustainable consumption and sustainable lifestyles. As individuals become familiar with the sharing of fashion products, they may also partake in the sharing of other products and services forming a part of the sharing economy such as homes and working spaces thereby contributing to creating a more sustainable planet.

REFERENCES

i. Agbo, F. J., Oyelere, S. S., Suhonen, J., & Tukiainen, M. (2021). Scientific Production and Thematic Breakthroughs in Smart Learning Environments: A Bibliometric Analysis. Smart Learning Environments, 8(1), 1–25. https://doi.org/10.1186/s40561-020-00145-4

ii. Allied Market Research. (2023). Online Clothing Rental Market. https://www.alliedmarketresearch.com/online-clothing-rental-market#:~:text=The%20global%20online%20clothing%20rental,clothes%20for%20a%20specific%20time.

iii. Amasawa, E., Brydges, T., Henninger, C. E., & Kimita, K. (2023). Can Rental Platforms Contribute to More Sustainable Fashion Consumption? Evidence from a Mixed-Method Study. Cleaner and Responsible Consumption, 8, 100103. https://doi.org/10.1016/j.clrc.2023.100103

iv. Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for Comprehensive Science Mapping Analysis. Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

v. Armstrong, C. M., Niinimäki, K., Kujala, S., Karell, E., & Lang, C. (2015). Sustainable Product-Service Systems for Clothing: Exploring Consumer Perceptions of Consumption Alternatives in Finland. Journal of Cleaner Production, 97, 30–39. https://doi.org/10.1016/j.jclepro.2014.01.046

vi. Bamel, U., Pereira, V., Del Giudice, M., & Temouri, Y. (2022). The Extent and Impact of Intellectual Capital Research: A Two Decade Analysis. Journal of Intellectual Capital, 23(2), 375–400. https://doi.org/10.1108/JIC-05-2020-0142

vii. Bardhi, F., & Eckhardt, G. M. (2012). Access-Based Consumption: The Case of Car Sharing. Journal of Consumer Research, 39(4), 881–898. https://doi.org/10.1086/666376

viii. Becker-Leifhold, C., & Iran, S. (2018). Collaborative Fashion Consumption – Drivers, Barriers and Future Pathways. Journal of Fashion Marketing and Management, 22(2), 189–208. https://doi.org/10.1108/JFMM-10-2017-0109

ix. Becker-Leifhold, C. V. (2018). The Role of Values in Collaborative Fashion Consumption - A Critical Investigation through the Lenses of the Theory of Planned Behavior. Journal of Cleaner Production, 199, 781–791. https://doi.org/10.1016/j.jclepro.2018.06.296

x. Belk, R. (2014). You Are What You Can Access: Sharing and Collaborative Consumption Online. Journal of Business Research, 67(8), 1595–1600. https://doi.org/10.1016/j.jbusres.2013.10.001

xi. Boar, A., Bastida, R., & Marimon, F. (2020). A Systematic Literature Review. Relationships Between the Sharing Economy, Sustainability and Sustainable Development Goals. Sustainability, 12(17), 1–14. https://doi.org/10.3390/SU12176744

xii. Bodenheimer, M., Schuler, J., & Wilkening, T. (2022). Drivers and Barriers to Fashion Rental for Everyday Garments: An Empirical Analysis of A Former Fashion-Rental Company. Sustainability: Science, Practice, and Policy, 18(1), 344–356. https://doi.org/10.1080/15487733.2022.2065774

xiii. Bretas, V. P. G., & Alon, I. (2021). Franchising Research on Emerging Markets: Bibliometric and Content Analyses. Journal of Business Research, 133, 51–65. https://doi.org/10.1016/j.jbusres.2021.04.067

xiv. Callon, M., Courtial, J. P., & Laville, F. (1991). Co-word Analysis as a Tool for Describing the Network of Interactions Between Basic and Technological Research: The Case of Polymer Chemistry. Scientometrics, 22(1), 155–205. https://doi.org/10.1007/BF02019280

xv. Camacho-Otero, J., Boks, C., & Pettersen, I. N. (2019). User Acceptance and Adoption of Circular Offerings in the Fashion Sector: Insights from User-generated Online Reviews. Journal of Cleaner Production, 231, 928–939. https://doi.org/10.1016/j.jclepro.2019.05.162

xvi. Chi, T., Adesanya, O., Liu, H., Anderson, R., & Zhao, Z. (2023). Renting than Buying Apparel: U.S. Consumer Collaborative Consumption for Sustainability. Sustainability, 15(6), 4926. https://doi.org/10.3390/su15064926

xvii. Cobo, M. J., López-Herrera, A. G., Herrera-Viedma, E., & Herrera, F. (2011). An Approach for Detecting, Quantifying, and Visualizing the Evolution of a Research Field: A Practical Application to the Fuzzy Sets Theory Field. Journal of Informetrics, 5(1), 146–166. https://doi.org/10.1016/j.joi.2010.10.002

xviii. Costa, M. R. C., Silva, M. E., & Duarte, M. de F. (2024). Sustainable Consumption and Practice Theories: Connecting Elements of Clothing Sharing. Brazilian Business Review, 21(1), 1–25. https://doi.org/10.15728/bbr.2021.1182.en

xix. Deloitte. (2024). 2024 Gen Z and Millennial Survey. https://www.deloitte.com/content/dam/assets-shared/docs/campaigns/2024/deloitte-2024-genz-millennial-survey.pdf?dlva=1

xx. Dhiaf, M. M., Atayah, O. F., Nasrallah, N., & Frederico, G. F. (2021). Thirteen Years of Operations Management Research (OMR) Journal: A Bibliometric Analysis and Future Research Directions. Operations Management Research, 14(3–4), 235–255. https://doi.org/10.1007/s12063-021-00199-8

xxi. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

xxii. Duriau, V. J., Reger, R. K., & Pfarrer, M. D. (2007). A Content Analysis of the Content Analysis Literature in Organization Studies: Research Themes, Data Sources, and Methodological Refinements. Organizational Research Methods, 10(1), 5–34. https://doi.org/10.1177/1094428106289252

xxiii. Forbes. (2024, May). Fashion Rental Market Makes A Comeback—As Gen Z And Millennials Revive Brands Like Nuuly, Rent The Runway. https://www.forbes.com/sites/hyunsoorim/2024/05/28/fashion-rental-market-makes-a-comeback-as-gen-z-and-millennials-revive-brands-like-nuuly-rent-the-runway/

xxiv. Future Market Insights. (2025). Online Clothing Rental Market Size, Share & Forecast 2035. https://www.futuremarketinsights.com/reports/online-clothing-rental-market#:~:text=Online clothing -rent

xxv. Gaur, A., & Kumar, M. (2018). A Systematic Approach to Conducting Review Studies: An Assessment of Content Analysis in 25 years of IB Research. Journal of World Business, 53(2), 280–289. https://doi.org/10.1016/j.jwb.2017.11.003

xxvi. Hamari, J., Sjöklint, M., & Ukkonen, A. (2016). The Sharing Economy: Why People Participate in Collaborative Consumption. Journal of the Association for Information Science and Technology, 67(9), 2047–2059. https://doi.org/10.1002/asi.23552

xxvii. Henninger, C. E., Taylor Brydges, Iran, S., & Vladimirova, K. (2021). Collaborative Fashion Consumption – A Synthesis and Future Research Agenda. Journal of Cleaner Production, 319, 1–12. https://doi.org/10.1016/j.jclepro.2021.128648

xxviii. Hirsch, J. E. (2005). An Index to Quantify an Individual's Scientific Research Output. Proceedings of the National Academy of Sciences, 102(46), 16569–16572. https://doi.org/10.1073/pnas.0507655102

xxix. Holtström, J., Bjellerup, C., & Eriksson, J. (2019). Business Model Development for Sustainable Apparel Consumption: The Case of Houdini Sportswear. Journal of Strategy and Management, 12(4), 481–504. https://doi.org/10.1108/JSMA-01-2019-0015

xxx. Indian Express. (2025). Luxury Made Affordable: Why Renting Is The Buzzword In The Fashion Industry. https://indianexpress.com/article/et-al-express-insight/luxury-made-affordable-why-renting-is-the-buzzword-in-the-fashion-industry/

xxxi. Iran, S., Geiger, S. M., & Schrader, U. (2019). Collaborative Fashion Consumption – A Cross-Cultural Study Between Tehran and Berlin. Journal of Cleaner Production, 212, 313–323. https://doi.org/10.1016/j.jclepro.2018.11.163

xxxii Iran, S., & Schrader, U. (2017). Collaborative Fashion Consumption and Its Environmental Effects. Journal of Fashion Marketing and Management, 21(4), 468–482. https://doi.org/10.1108/JFMM-09-2016-0086

xxxiii. Jain, S., & Mishra, S. (2020). Luxury Fashion Consumption in Sharing Economy: A Study of Indian Millennials. Journal of Global Fashion Marketing, 11(2), 171–189. https://doi.org/10.1080/20932685.2019.1709097

xxxiv. Johnson, E., & Plepys, A. (2021). Product-Service Systems and Sustainability: Analysing the Environmental Impacts of Rental Clothing. Sustainability, 13(4), 1–30. https://doi.org/10.3390/su13042118

xxxv. Johnson, K. K. P., Mun, J. M., & Chae, Y. (2016). Antecedents to Internet Use to Collaboratively Consume Apparel. Journal of Fashion Marketing and Management, 20(4), 370–382. https://doi.org/10.1108/JFMM-12-2015-0092

xxxvi. Khitous, F., Urbinati, A., & Verleye, K. (2022). Product-Service Systems: A Customer Engagement Perspective in the Fashion Industry. Journal of Cleaner Production, 336, 130394. https://doi.org/10.1016/j.jclepro.2022.130394

xxxvii. Kim-Vick, J., & Cho, E. (2024). Gen Z Consumers' Intention to Adopt Online Collaborative Consumption of Second-hand Luxury Fashion Goods. Journal of Global Fashion Marketing, 15(4), 440–458. https://doi.org/10.1080/20932685.2024.2339230

xxxviii. Lang, C. (2018). Perceived Risks and Enjoyment of Access-Based Consumption: Identifying Barriers and Motivations to Fashion Renting. Fashion and Textiles, 5(1), 1–18. https://doi.org/10.1186/s40691-018-0139-z

xxxix. Lang, C., & Armstrong, C. M. J. (2018a). Collaborative Consumption: The Influence of Fashion Leadership, Need for Uniqueness, and Consumers' Adoption of Clothing Renting and Swapping. Sustainable Production and Consumption, 13, 37–47. https://doi.org/10.1016/j.spc.2017.11.005

xl. Lang, C., & Armstrong, C. M. J. (2018b). Fashion Leadership and Intention toward Clothing Product-Service Retail Models. Journal of Fashion Marketing and Management, 22(4), 571–587. https://doi.org/10.1108/JFMM-12-2017-0142

xli. Lang, C., Li, M., & Zhao, L. (2020). Understanding Consumers' Online Fashion Renting Experiences: A Text-Mining Approach. Sustainable Production and Consumption, 21, 132–144. https://doi.org/10.1016/j.spc.2019.12.003

xlii. Lang, C., Seo, S., & Liu, C. (2019). Motivations and Obstacles for Fashion Renting: A Cross-Cultural Comparison. Journal of Fashion Marketing and Management, 23(4), 519–536. https://doi.org/10.1108/JFMM-05-2019-0106

xliii. Lang, C., & Zhang, R. (2024). Motivators of Circular Fashion: The Antecedents of Chinese Consumers' Fashion Renting Intentions. Sustainability (Switzerland), 16(5), 1–17. https://doi.org/10.3390/su16052184

xliv. Laudien, S. M., Manuel Guaita Martínez, J., & María Martín Martín, J. (2023). Business Models Based on Sharing Fashion and Accessories: Qualitative-Empirical Insights into a New Type of Sharing Economy Business Models. Journal of Business Research, 157, 113636. https://doi.org/10.1016/j.jbusres.2022.113636

xlv. Lee, S. H. N., & Chow, P. S. (2020). Investigating Consumer Attitudes and Intentions Toward Online Fashion Renting Retailing. Journal of Retailing and Consumer Services, 52, 1–9. https://doi.org/10.1016/j.jretconser.2019.101892

xlvi. Lim, W. M., Kumar, S., & Donthu, N. (2024). How to Combine and Clean Bibliometric Data and Use Bibliometric Tools Synergistically: Guidelines Using Metaverse Research. Journal of Business Research, 182, 1–31. https://doi.org/10.1016/j.jbusres.2024.114760

xlvii. McKinney, E., & Shin, E. (2016). Exploring Criteria Consumers Use in Evaluating Their Online

Formal Wear Rental Experience: A Content Analysis of Online Reviews. Clothing and Textiles Research Journal, 34(4), 272–286. https://doi.org/10.1177/0887302X16654269

xlviii. McKinsey & Company. (2023). What Is Fast Fashion? (pp. 1–5). https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-fast-fashion

xlix. Mishra, S., Jain, S., & Jham, V. (2021). Luxury Rental Purchase Intention Among Millennials – A Cross-national Study. Thunderbird International Business Review, 63(4), 503–516. https://doi.org/10.1002/tie.22174

l. Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. Annals of Internal Medicine, 151(4), 264–269. https://doi.org/10.7326/0003-4819-151-4-200908180-00135

li. Möhlmann, M. (2015). Collaborative Consumption: Determinants of Satisfaction and the Likelihood of Using a Sharing Economy Option Again. Journal of Consumer Behaviour, 14(3), 193–207. https://doi.org/10.1002/cb

lii. Monticelli, A., & Costamagna, M. (2023). Environmental Assessment of the Rental Business Model: A Case Study for Formal Wear. Environment, Development and Sustainability, 25(8), 7625–7643. https://doi.org/10.1007/s10668-022-02363-x

liii. Mumu, J. R., Saona, P., Mamun, M. A. Al, & Azad, M. A. K. (2022). Is Trust Gender Biased? A Bibliometric Review of Trust in E-Commerce. Journal of Internet Commerce, 21(2), 217–245. https://doi.org/10.1080/15332861.2021.1927437

liv. Myin, M. T., Su, J., Wu, H. (Jeff), & Shen, H. (2023). Investigating the Determinants of Using Clothing Subscription Rental Services: A Perspective from Chinese Young Consumers. Young Consumers, 24(1), 95–113. https://doi.org/10.1108/YC-06-2022-1547

lv. Niknejad, N., Ismail, W., Bahari, M., Hendradi, R., & Salleh, A. Z. (2021). Mapping the Research Trends on Blockchain Technology in Food and Agriculture Industry: A Bibliometric Analysis. Environmental Technology and Innovation, 21, 101272. https://doi.org/10.1016/j.eti.2020.101272

lvi. Noe, H., & Hyun, J. (2024). Why Do and Why Don't Consumers Use Fashion Rental Services? A Consumption Value Perspective. Journal of Fashion Marketing and Management, 28(3), 566–580. https://doi.org/10.1108/JFMM-07-2023-0168

lvii. Palgan, Y. V., Zvolska, L., & Mont, O. (2017). Sustainability Framings of Accommodation Sharing. Environmental Innovation and Societal Transitions, 23, 70–83. https://doi.org/10.1016/j.eist.2016.12.002

lviii. Palomo-Domínguez, I., Elías-Zambrano, R., & Álvarez-Rodríguez, V. (2023). Gen Z's Motivations Towards Sustainable Fashion and Eco-Friendly Brand Attributes: The Case of Vinted. Sustainability (Switzerland), 15(11). https://doi.org/10.3390/su15118753

lix. Park, H., & Armstrong, C. M. J. (2017). Collaborative Apparel Consumption in the Digital Sharing Economy: An Agenda for Academic Inquiry. International Journal of Consumer Studies, 41(5), 465–474. https://doi.org/10.1111/ijcs.12354

lx. Park, H., & Armstrong, C. M. J. (2019). Is Money the Biggest Driver? Uncovering Motives for Engaging in Online Collaborative Consumption Retail Models for Apparel. Journal of Retailing and Consumer Services, 51, 42–50. https://doi.org/10.1016/j.jretconser.2019.05.022

lxi. Park, H., & Lee, M.-Y. (2022). The Two-Sided Effect of the COVID-19 Pandemic on Online Apparel Renting. Sustainability (Switzerland), 14(24), 1–16. https://doi.org/10.3390/su142416771

lxii. Pedersen, E. R. G., & Netter, S. (2015). Collaborative Consumption: Business Model Opportunities and Barriers for Fashion Libraries. Journal of Fashion Marketing and Management, 19(3), 258–273. https://doi.org/10.1108/JFMM-05-2013-0073

lxiii. Pham, H. T., Hoang, K. T., Nguyen, T. T., Do, P. H., & Mar, M. T. C. (2021). Sharing Economy: Generation Z's Intention Toward Online Fashion Rental in Vietnam. Journal of Asian Finance, Economics and Business, 8(3), 997–1007. https://doi.org/10.13106/jafeb.2021.vol8.no3.0997

lxiv. Ruan, Y., Xu, Y., & Lee, H. (2022). Consumer Motivations for Luxury Fashion Rental: A Second-Order Factor Analysis Approach. Sustainability (Switzerland), 14(12), 1–16. https://doi.org/10.3390/su14127475

lxv. Savelli, E., Francioni, B., Curina, I., & Cioppi, M. (2024). Promoting Access-based Consumption Practices through Fashion Renting: Evidence from Italy. Journal of Consumer Marketing, 41(1), 61–77. https://doi.org/10.1108/JCM-02-2023-5843

lxvi. Schor, J. (2014). Debating the Sharing Economy. Journal of Self-Governance and Management

Economics, 4(3), 7–22. https://doi.org/10.22381/jsme4320161

lxvii. Shrivastava, A., Jain, G., Kamble, S. S., & Belhadi, A. (2021). Sustainability through Online Renting Clothing: Circular Fashion Fueled by Instagram Micro-celebrities. Journal of Cleaner Production, 278, 1–35. https://doi.org/10.1016/j.jclepro.2020.123772

lxviii. Statista Research Department. (2024). Rental Apparel Market Revenue Worldwide 2019–2026. https://www.statista.com/statistics/1195613/rental-apparel-market-revenue-worldwide/

lxix. Tao, Q., & Xu, Y. (2020). Consumer Adoption of Fashion Subscription Retailing: Antecedents and Moderating Factors. International Journal of Fashion Design, Technology and Education, 13(1), 78–88. https://doi.org/10.1080/17543266.2020.1737247

lxx. Tukker, A. (2004). Eight Types of Product–Service System: Eight Ways to Sustainability? Experiences from SusProNet. Business Strategy and the Environment, 13(4), 246–260.

lxxi. Ulrich, I., Cacho-Elizondo, S., Damay, C., & Loussaïef, L. (2024). A Practice Theory Perspective on Apparel Sharing Consumption Models Exploring New Paths of Consumption in France and Mexico. Journal of Retailing and Consumer Services, 77, 1–15. https://doi.org/10.1016/j.jretconser.2023.103626

lxxii. van Eck, N. J., & Waltman, L. (2010). Software Survey: VOSviewer, A Computer Program for Bibliometric Mapping. Scientometrics, 84(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

lxxiii. Westerberg, C., & Martinez, L. F. (2023). Young German Consumers' Perspectives of Rental Fashion Platforms. Young Consumers, 24(3), 309–330. https://doi.org/10.1108/YC-06-2022-1543

lxxiv. Xu, Y., Chen, Y., Burman, R., & Zhao, H. (2014). Second-hand Clothing Consumption: A Cross-cu -ltural Comparison Between American and Chinese Young Consumers. International Journal of Consumer Studies, 38(6), 670–677. https://doi.org/10.1111/ijcs.12139

lxxv. Zamani, B., Sandin, G., & Peters, G. M. (2017). Life Cycle Assessment of Clothing Libraries: Can Collaborative Consumption Reduce the Environmental Impact of Fast Fashion? Journal of Cleaner Production, 162, 1368–1375. https://doi.org/10.1016/j.jclepro.2017.06.128

lxxvi. Zupic, I., & Cater, T. (2015). Bibliometric Methods in Management and Organization.Organization -al Research Methods, 18(3), 429–472. https://doi.org/10.1177/1094428114562629

The Study of Factors Influencing the Adoption of mHealth Applications among the Consumers of Health Services.

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ABSTRACT

Mobile-enabled health technologies let individuals obtain clinical guidance and assessments without an in-person visit and give public-health agencies a powerful channel for distributing programmes throughout a community. This study investigates how users' motivation to avoid perceived threats interacts with their attitudes to shape intentions to adopt mobile-health (mHealth) apps. To capture both acceptance and avoidance dynamics, the research unites the Technology Acceptance Model (TAM) with Technology Threat Avoidance Theory (TTAT). In the integrated framework, threat- and coping-appraisal processes feed avoidance motivation, whereas perceived ease of use and perceived usefulness foster a favourable attitude. The hypothesised paths are assessed with Partial Least Squares Structural Equation Modelling (PLS-SEM). By highlighting the most influential mHealth determinants from the perspective of key stakeholders, the findings offer actionable guidance for practitioners and policymakers overseeing mHealth roll-outs.

KEYWORDS

mHealth, TAMTTAT, Self-efficacy, Adoption intention

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INTRODUCTION

mHealth denotes delivering healthcare services through wireless devices to improve individual health outcomes. mHealth service could be as basic as using the SMS function of a mobile phone to send health-related alerts to complex services, such as using built-in mobile sensors to interpret clinical data (PricewaterhouseCoopers, n.d. 2024). In the current landscape, India is grappling with the challenge of making primary healthcare accessible to all, with a noticeable disparity between urban and rural areas, and private and subsidized healthcare. This has led to a significant burden on healthcare costs for the population. However, the emergence of mobile healthcare, or mHealth, offers hope. It has the potential to not only reduce healthcare costs but also bridge the gap in healthcare access, particularly in underserved areas (Healthcare at Your Fingertips: Case of mHealth in India. | Centre For Civil Society, n.d. 2024). India's digital landscape is rapidly evolving. In 2023, the country had over 1.2 billion internet users, the second-largest worldwide. A staggering 1.05 billion accessed the internet through mobile phones, predicted to reach 1.2 billion by 2050 (India: Mobile Phone Internet Users 2050 | Statista, n.d. 2024). This digital revolution is also reflected in the healthcare sector, with over 245 million health and fitness app downloads nationwide in 2021. The primary focus areas of Indians while using these apps were meditation, mental health, and fitness. However, despite the high internet and mobile phone penetration, the adoption of mHealth services in India is still relatively low. This could result from a variety of factors such as unawareness, information on data privacy concerns and the digital divide between urban and rural areas. Addressing these barriers is critical to drive mHealth uptake in India; this underscores the significance of the barriers that stand in the way of mHealth adoption in India which need to be addressed if we are to promote the introduction of mHealth (Rajak & Shaw, 2021). Intellectual mHealth involves the integration of advanced technologies like AI, blockchain, and cloud computing into mHealth offerings. On another note, machine learning has found utility in speech recognition for dysarthria patients (Swain et al., 2023). The potential applications of intellectual mHealth are far-reaching: clinical data collection, provision of health services to both practitioners and patients, research enhancement and support for healthcare education, as well as real-time patient monitoring (Addotey-Delove et al., 2022b).

A growing body of research underlines the importance of studying mHealth adoption among India's digitally native 18–35 age group due to their high technological fluency and proactive health behaviors (DeSouza et al., 2014). In India, where smartphone penetration continues to surge among young adults, leveraging mHealth has been shown to significantly enhance health promotion, disease prevention, and chronic disease management outcomes (Agarwal et al., 2023). Understanding adoption drivers enables developers to design scalable, user-centered apps that resonate with India's diverse youth demographic. The study presents an integrated model incorporating the Technology Acceptance Model (TAM, Davis 1989) and Technology Threat Avoidance Theory (TAAT) to elucidate the antecedents affecting intellectual healthcare technology adoption. TAM predicted perceived ease of use and perceived usefulness to determine the use intention, which further leads to the use of technology (Silva, 2015). Technology Threat Avoidance Theory (TTAT; Liang & Xue, 2009) discusses why individuals or organizations may feel reluctant to adopt or engage in a new technology or innovation.

LITERATURE REVIEW

Technological advances are reshaping how healthcare is delivered. Digital tools allow organizations to shift away from slow, centrally controlled workflows toward more agile, decentralized operations, provided the underlying business model still generates sustainable returns (Black & Cherrington, 2022). According to Tajudeen et al. (2022), mobile health (mHealth) services function as communication platforms that expand key care features, giving patients greater autonomy in selecting and managing their own treatment options. While strong marketing visibility encourages uptake, factors such as app complexity and limited use cases can deter adoption. Tajudeen et al. (2022) ultimately conclude that personal motivation is the primary catalyst driving consumers to embrace mHealth. In a wide-ranging review of 427 studies, Goel and Taneja (2023) catalogued the latest innovations in phone-based health services, whereas Riley et al. (2011) argue that prevailing theoretical models still fail to capture all the organizational factors influencing adoption.

Considering Table 1, the contemporary mHealth adoption literature paints a multifaceted picture in which classic technology-acceptance logics interweave with risk–benefit appraisals, quality judgments, and demographic contingencies. Early empirical work by Guo et al. (2015) used Protection Motivation Theory (PMT) to show that Chinese smartphone users' coping appraisals (self-efficacy and response efficacy) outweighed threat appraisals in shaping intention. This insight foreshadowed a wave of studies arguing that perceived capability and perceived usefulness trump purely fear-based drivers. For example, Mouloudj et al. (2023) extended the Technology Acceptance Model (TAM) with self-efficacy and trust in an Algerian consumer sample, confirming that perceived ease of use and trust jointly bolster usefulness perceptions, which in turn drive adoption intention.

Parallel efforts refined the Unified Theory of Acceptance and Use of Technology. Palas et al. (2022) verified that performance expectancy, effort expectancy, and hedonic motivation explain 71 % of variation in Bangladeshi elders' intention when augmented with service quality and perceived

quality of life. Yang et al. (2024), working with a large Indonesian Telegram cohort, showed that perceived product value moderates most UTAUT2 paths, implying that value framing can amplify technology beliefs. A generational lens emerged in Rahman and Uddin (2025): their SEM-ANN study of Malaysian millennials found habit and social influence to be the strongest predictors of intention, but post-hoc importance-performance mapping revealed effort expectancy as the most actionable managerial lever.

Table 1: mHealth Studies

Study	Context / Sample	Model Highlights
Palas et al. (2022) – "Factors Influencing the Elderly's Adoption of mHealth"	Bangladesh, elders (n = 493)	UTAUT2 + Service Quality & Quality of Life predictors
Yang et al. (2024) – "Predicting m-Health Acceptance"	Indonesian Telegram users (n = 2 068)	Moderating role of Perceived Product Value within UTAUT
Chai et al. (2025) – "mHealth Adoption Intention Among Gen Y"	Malaysian millennials	Integrated UTAUT + Health Belief Model (HBM); analysed via SEM-ANN-IPMA
Vu et al. (2022) – "Self-Efficacy & Privacy Concerns in mHealth"	China	Adds self-efficacy & privacy constructs to UTAUT for app adoption
Lee et al. (2024) – "mHealth Adoption & Mental Well-Being"	Multinational survey	Modified UTAUT2; shows links to psychological well-being
Chiu, Won & Chen (2025) – "Older Adults' Adoption Behaviour of mHealth Apps"	US seniors (n = 600)	Technology Readiness + PMT; coping appraisals trump threat appraisals
Guo et al. (2015) – "Investigating m-Health Acceptance from a PMT Perspective"	Chinese smartphone users	Threat & coping appraisals predict adoption intention
Marikyan & Papagiannidis (2020) – "Health Concerns About Emerging Wearables"	UK consumers	Applies TTAT to explain avoidance vs. adoption of mHealth wearables
Zhao et al. (2024) – "Quality Factors Affecting Continued Use of mHealth Apps"	Ethnic-minority users in Southwest China	ECM + PLS-SEM & ANN hybrid analysis
Sultana et al. (2024) – "Community Health Workers' Continuance of mHealth Applications"	Bangladesh CHWs	ECM + IS-Success model; highlights system quality & confirmation science
Fan et al. (2023) – "Comprehensive Picture of Factors Affecting mHealth Use"	TAM + privacy-concern & demographic moderators	Eight-country SEM study (n = 1 669); digital literacy strongest predictor
JMIR Human Factors (2024) – "Provider Adoption of mHealth in Rural Care"	TAM × TPB × organisational factors	Illuminates provider-side barriers in low-resource settings, human factors.

Risk and security concerns remain prominent yet do not necessarily deter adoption if counter-balanced by capability beliefs. Liu et al. (2022) integrated privacy concerns into UTAUT and observed that privacy exerts an indirect negative effect—weak enough to be offset by self-efficacy and performance expectancy among Chinese users. At the same time, Chiu, Won, and Chen (2025) combined Technology Readiness with PMT to explore older US adults: technology readiness dimensions influenced coping more than threat appraisals, underlining the importance of empowerment narratives when targeting seniors.

Research on post-adoption behaviour now runs parallel to the early adoption literature. For instance, Deng et al. (2024) blended the Expectation–Confirmation Model with an artificial-neural-network approach and showed that, for ethnic-minority Chinese users, a combination of confirmation, perceived service quality and overall satisfaction is decisive for ongoing engagement. Tian and Wu (2022) reached a similar conclusion with older adults living with chronic illness: by integrating ECM and UTAUT they found that confirmation bolsters both effort and performance expectations, which together lead to sustained use. Evidence from the supply side paints a different picture. Weichelt et al. (2024) observed that in rural U.S. healthcare organisations, management backing and the perceived benefit to patients outweigh effort expectancy, implying that institutional drivers diverge from those affecting consumers.

Hybrid models underscore the idea that a single theory cannot fully explain mHealth dynamics. Fan et al. (2023) combined TAM with privacy concerns and demographic moderators across eight nations, concluding that digital literacy is the dominant predictor of willingness to adopt. Looking beyond individual factors, Marikyan and Papagiannidis (2020) applied Technology Threat Avoidance Theory to wearables and found that adoption and avoidance can exist side by side when users perceive adequate safeguards.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the most widely used frameworks for predicting user acceptance of information systems. TAM posits that two primary beliefs—perceived ease of use and perceived usefulness—directly influence users' attitudes toward technology, which in turn affect their behavioral intentions to adopt (Davis, 1989; Venkatesh & Davis, 2000). Numerous studies have validated TAM across various contexts, demonstrating that when users perceive a technology as easy to use and useful, they are more likely to develop positive attitudes and intentions toward its adoption (Venkatesh & Bala, 2008).

Technology Threat Avoidance Theory (TTAT)

While TAM effectively explains utilitarian motivations, it does not address users' concerns about risks or threats. The Technology Threat Avoidance Theory (TTAT), developed by Liang and Xue (2010), addresses this gap by focusing on how individuals respond to perceived threats in technology use, particularly in security and privacy contexts. TTAT introduces constructs such as self-efficacy—the belief in one's ability to execute threat avoidance behaviors—and perceived effectiveness—the belief that these behaviors will successfully mitigate threats (Liang & Xue, 2010; Ifinedo, 2012). These constructs are critical in contexts where security, privacy, or risk are salient, as they shape both attitudes and intentions toward adopting protective technologies.

Integrated Model: TAM and TTAT

Integrating TAM and TTAT provides a more holistic understanding of technology adoption. Recent research supports the inclusion of threat avoidance constructs alongside traditional acceptance variables. For example, Ifinedo (2012) found that both self-efficacy and perceived effectiveness significantly influenced attitudes toward security-related technologies, complementing the effects of perceived usefulness and ease of use. Similarly, Anderson and Agarwal (2010) demonstrated that users' confidence in their ability to manage threats and their belief in the effectiveness of protective actions were pivotal in shaping positive attitudes and intentions.

The adoption of mobile health (mHealth) technologies has gained prominence due to their potential to improve healthcare accessibility, efficiency, and patient engagement. The theoretical foundation of mHealth adoption is frequently examined using the Technology Acceptance Model (TAM), Social Cognitive Theory, and related frameworks. The following literature supports the hypothesis that perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness significantly influence users' attitudes, which in turn influence mHealth adoption intentions. Perceived ease of use refers to the degree to which a person believes that using a system would be free of effort. It is a core component of TAM and has been empirically linked to user attitudes toward technology. In a recent study, Huang et al. (2025) found that PEOU significantly influenced clinicians' positive perceptions of mHealth tools, particularly in image-based assessments in remote diagnostics. Users reported that simple and intuitive interfaces increased their willingness to engage with mHealth apps (Huang et al., 2025). This supports earlier findings by Davis (1989), emphasizing the centrality of PEOU in shaping attitudes. Perceived usefulness, another TAM construct, is defined as the degree to which a person believes that using a system enhances their performance. PU has been consistently shown to shape favorable user attitudes. In the study by Ferreira and Caldeira (2024), perceived usefulness emerged as a dominant factor influencing healthcare professionals' and patients' willingness to use mobile health apps.

Apps perceived as beneficial in improving decision-making and reducing time for diagnosis elicited stronger positive attitudes toward continued use (Ferreira & Caldeira, 2024). Self-efficacy is an individual's belief in their ability to perform specific tasks. Bandura's Social Cognitive Theory posits that self-efficacy directly influences behavior and attitudes. Ferreira and Caldeira (2024) highlighted that patient confidence in their ability to navigate mHealth apps was significantly associated with favorable attitudes. Those with higher digital self-efficacy were more likely to adopt and recommend mHealth tools.

Perceived effectiveness relates to users' belief that mHealth applications achieve desired health outcomes. Empirical findings suggest that effectiveness perceptions are central to the evaluation of technological interventions. Huang et al. (2025) reported that users who found mobile imaging apps effective in real-time trauma assessment held a more positive attitude towards adoption. The alignment of app functionality with user expectations for clinical effectiveness is crucial in this context. Attitude acts as a mediating variable between beliefs and behavioral intention. According to both studies reviewed, a favorable attitude was the most consistent predictor of mHealth adoption intention. Positive perceptions of usefulness, ease of use, and confidence culminated in a strong intention to use these technologies in routine healthcare practices. Based on the above, the following hypotheses are proposed and represented in Figure 1. The presented model reflects this integration: perceived ease of use and perceived usefulness (from TAM), along with self-efficacy and perceived effectiveness (from TTAT), are posited to influence attitude, which subsequently predicts adoption intention.

H1: Perceived ease of use significantly influences attitude.

H2: Perceived usefulness significantly influences attitude.

H3: Self-efficacy significantly influences attitude.

H4: Perceived effectiveness significantly influences attitude.

H5: Attitude significantly influences mHealth adoption intention.

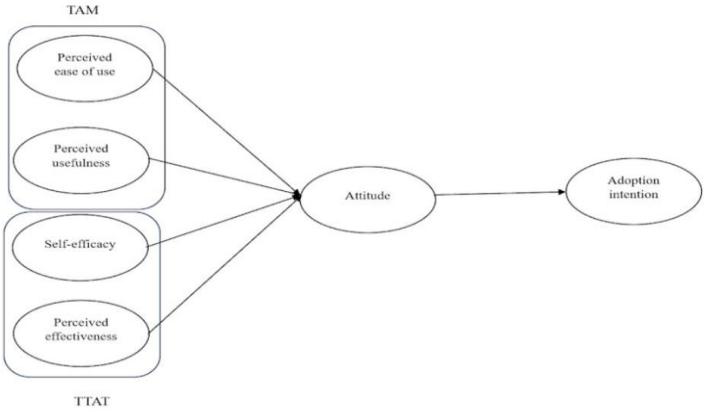

Figure 1: Conceptual framework

METHODOLOGY

A cross-sectional survey-based quantitative research design was employed. This design allows for the collection of primary data from a large sample at a single point in time, making it ideal for studying relationships among constructs such as perceptions, attitudes, and behavioral intentions. A structured questionnaire, adapting the variables from literature was used to measure the constructs in the hypotheses:

Table 2: Measurement Scale

Construct	Measurement Source	Scale
Perceived Ease of Use (PEOU)	Davis (1989) – TAM	5 point Likert scale
Perceived Usefulness (PU)	Davis (1989) – TAM	5 point Likert scale
Self-Efficacy (SE)	Liu et al. (2020)	5 point Likert scale
Perceived Effectiveness (PE)	Adapted from Lin (2007), Venkatesh et al. (2012)	5 point Likert scale
Attitude toward mHealth (AT)	Ajzen & Fishbein (1980)	5 point Likert scale
Adoption Intention (INT)	Venkatesh et al. (2003)	5 point Likert scale

Respondents include Individuals who have used or are potential users of mobile health (mHealth) applications (e.g., patients, general users, and healthcare professionals). The qualifying questions for respondents were related to their awareness and use of any of the fitness trackers, telemedicine apps, medication reminders, or health monitoring apps in the past 6 months. A convenience sampling approach has been used to ensure representation across age groups, gender, health status, and mHealth usage experience. 343 respondents participated in the study. Sample size determination was based on Hair et al.'s rule: 10 respondents per observed variable. Data was collected online via survey platforms, distributed through social media, health forums, or mHealth platforms. Informed consent was obtained prior to participation.

Non-response bias

The reported response rate was 69%, which is below the 85% threshold. It is crucial to test for non-response error to ensure the external validity of the study. The sample was divided into three distinct categories: early respondents (those who responded without a reminder), late respondents, and non-respondents. The χ^2 test confirms that the results of the groups are similar based on the respondents' characteristics and the constructs considered in the study, indicating that there is no significant non-response bias.

Common method bias

Common method bias is often a concern in cross-sectional studies where respondents report on their own experiences. To assess this, we conducted a Harman single-factor test on the constructs involved. The results showed that no single factor accounted for more than 50 percent of the variance across all variables, indicating that our dataset does not exhibit common method bias.

Demographic Profile

The demographic profile (Table 3) of the respondents (N = 343) reveals a predominance of male participants, accounting for 58.60%, while females comprised 41.39% of the sample. This indicates a slightly higher inclination or accessibility toward mHealth applications among males in the studied population. In terms of age distribution, individuals between 26–35 years represented the majority (51.89%), closely followed by those aged 18–25 years (48.10%). This suggests that mHealth usage is more prevalent among younger adults, potentially due to their higher familiarity with mobile technologies and proactive health-seeking behaviors. Educational qualifications indicate that over half of the respondents (53.93%) were postgraduates, with graduates forming 40.81% and a smaller proportion (5.24%) falling into other categories. This reflects a user base that is relatively well-educated, aligning with previous findings that suggest education level significantly influences digital health technology adoption. Regarding the purpose of mHealth use, the majority (64.43%) reported using mHealth for patient-centric services such as self-care and engagement, whereas 35.56% utilized it for provider-supporting tools aimed at clinical practice. This indicates a strong preference for personal health management tools among users, emphasizing the role of mHealth in enabling individuals to monitor and manage their own health proactively. Collectively, these insights underscore the growing reliance on mHealth among young, educated individuals, particularly for self-directed healthcare support.

Table 3: Demographic Profile

	Number	Percentage (%)
Gender		
Female	142	41.39
Male	201	58.60
Age		
18-25	165	48.10
26-35	178	51.89
Education Qualification		
Graduate	140	40.81
Postgraduate	185	53.93
Others	18	5.24
Purpose for mHealth		
Patient-centric Services (Self-care, engagement)	221	64.43
Provider-supporting tools (Clinical Practice)	122	35.56
TOTAL	343	100

RESULTS

Partial Least Squares Structural Equation Modelling (PLS-SEM) is the most appropriate analytic technique for this investigation because it excels at estimating intricate frameworks that contain many latent variables and indicators, yet prioritise prediction. Smart PLS 3 has been used for analysis. Unlike covariance-based SEM, PLS-SEM performs well with modest samples and data that fall short of strict multivariate-normality requirements. This makes it ideal for an emerging research domain such as mobile-health adoption, where representative data can be limited and distributional assumptions are rarely satisfied. The approach evaluates the measurement model and the structural paths in a single procedure, letting researchers verify construct reliability and validity while simultaneously testing hypothesised relationships among latent factors. Moreover, PLS-SEM accommodates both reflective and formative indicators and remains stable in the presence of multicollinearity, features that map neatly onto the mixed construct types and overlapping psychological and technological drivers examined here. Given the study's exploratory stance and its aim to predict how perceptions translate into usage intentions, PLS-SEM offers the necessary methodological flexibility and statistical power.

Measurement Model

The measurement model (Table 4) results provide strong evidence supporting the reliability and validity of the constructs used in the study. For the Perceived Ease of Use (PEOU) construct, all indicator loadings range between 0.763 and 0.884, which surpasses the recommended threshold of 0.70, indicating high indicator reliability. The Average Variance Extracted (AVE) is 0.735, confirming convergent validity, while Composite Reliability (CR = 0.867) and Cronbach's Alpha (α = 0.855) reflect excellent internal consistency. Similarly, Perceived Usefulness (PU) shows acceptable loadings (0.711 to 0.854), with AVE = 0.635, CR = 0.844, and α = 0.722—all supporting its reliability and validity.

In the case of Self-Efficacy (SE), three items (SE1 to SE3) load well, but SE4 has a very low loading of 0.237, indicating it does not adequately measure the construct and should be removed. Despite this, the construct's AVE (0.611), CR (0.799), and α (0.655) remain within acceptable limits, although the reliability would likely improve upon excluding SE4. For Perceived Effectiveness (PEF), all items have acceptable loadings (0.682–0.777), and the construct exhibits good convergent validity (AVE = 0.714) and reliability (CR = 0.775, α = 0.757). The Attitude (AT) construct shows high internal consistency, with loadings above 0.762, AVE = 0.876, CR = 0.877, and α = 0.852, although the exceptionally high AVE warrants a recheck. Lastly, the Adoption Intention (AI) construct performs well, with item loadings between 0.761 and 0.778, an AVE of 0.722, CR = 0.782, and α = 0.797, confirming its robust measurement properties.

Table 4: Measurement Model

Construct	Item	Loading	AVE	CR	α
Perceived Ease of Use (PEOU)	PEOU1	0.852	0.735	0.867	0.855
	PEOU2	0.763			
	PEOU3	0.883			
	PEOU4	0.854			
Perceived Usefulness (PU)	PU1	0.854	0.635	0.844	0.722
	PU2	0.833			
	PU3	0.711			
Self-Efficacy (SE)	SE1	0.711	0.611	0.799	0.655
	SE2	0.821			
	SE3	0.865			
	SE4	0.237			
Perceived effectiveness (PEF)	AM1	0.776	0.714	0.775	0.757
	AM2	0.777			
	AM3	0.682			
Attitude (AT)	AT1	0.779	0.876	0.877	0.852
	AT2	0.762			
	AT3	0.874			
Adoption intention (AI)	AI1	0.761	0.722	0.782	0.797
	AI2	0.766			
	AI3	0.773			
	AI4	0.778			

Structural Model

The structural model results (Table 5) confirm that all proposed relationships among the constructs are statistically significant and positively associated. Perceived ease of use has a positive influence on attitude, as indicated by a path coefficient of 0.277 and a t-value of 3.515. This implies that when users find a mobile health (mHealth) application easy to use, they are more likely to develop a favorable attitude toward it. Similarly, perceived usefulness shows a significant positive effect on attitude, with a path coefficient of 0.387 and a t-value of 4.515, suggesting that users who perceive the app to be helpful in achieving health-related outcomes tend to have a more positive attitude.

Self-efficacy also demonstrates a strong influence on attitude, with a coefficient of 0.432 and a t-value of 5.242. This means that users who feel confident in their ability to use mHealth apps are more inclined to view them positively. Notably, perceived effectiveness has the strongest effect on attitude, with a path coefficient of 0.467 and a t-value of 6.424, highlighting that users' belief in the app's ability to deliver health benefits plays a critical role in shaping their attitude. Attitude, in turn, significantly influences adoption intention, as shown by a path coefficient of 0.332 and a t-value of 4.423. Although the effect size for this relationship is smaller, it still confirms that a positive attitude contributes to the intention to adopt mHealth technologies.

The model explains 58.6% of the variance in attitude and 42.8% in adoption intention, which are considered substantial and moderate, respectively. Furthermore, all constructs demonstrate predictive relevance, as reflected in Q^2 values above zero (0.347 for attitude and 0.284 for adoption intention). All variance inflation factor (VIF) values are well below the threshold of 3.3, indicating no multicollinearity issues. Overall, the structural model demonstrates good predictive strength and reliability in capturing the factors influencing mHealth adoption. The structural model is presented in Figure 2.

Table 5: Structural Model

Hypothesis	Relationship	Path Coefficient	t Value	Decision	VIF	f^2	Q^2	R^2
H1	PEOU→AT	0.277**	3.515	Accepted	1.354	0.088	0.347	0.586
H2	PU→AT	0.387**	4.515	Accepted	1.354	0.088		
H3	SE→AT	0.432**	5.242	Accepted	1.647	0.121		
H4	PEF→AT	0.467**	6.424	Accepted	1.448	0.262		
H5	AT→AI	0.332**	4.423	Accepted	1.323	0.043	0.284	0.428

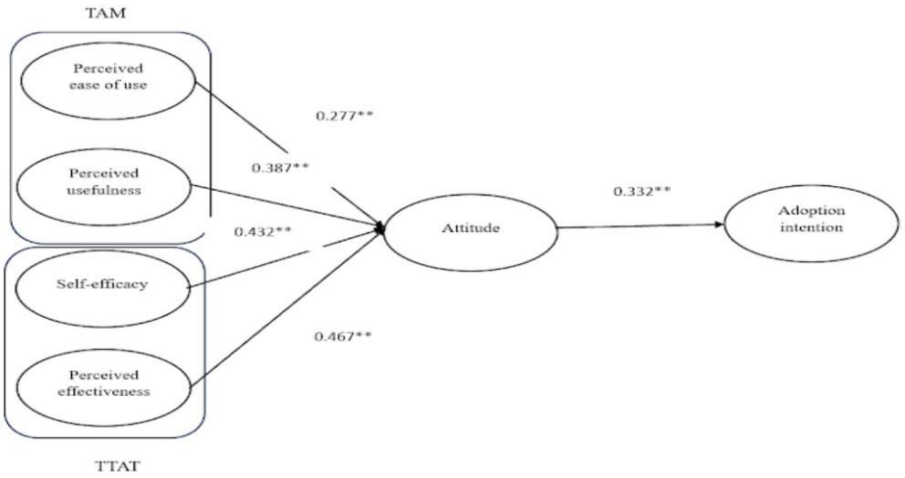

Figure 2: Structural model

DISCUSSION

The structural-path estimates shed nuanced light on what propels or hinders people's readiness to embrace mobile-health apps. First, the robust, positive link between perceived ease of use (PEOU) and user attitude reiterates Davis's original Technology Acceptance Model (1989), yet the present context adds specificity: when navigation flows are friction-free, screen layouts are uncluttered, and onboarding cues are self-explanatory, potential users translate that experiential comfort into an affective "thumbs-up." Contemporary mHealth evidence echoes this view; Alam et al. (2021) showed that even marginal gains in interface clarity measurably boost attitudinal scores among chronic-care patients. Perceived usefulness (PU) proved similarly consequential. In health settings, usefulness is rarely abstract; it materialises as faster symptom logging, personalised feedback loops, or easier appointment scheduling. The data confirm that such concrete benefits strongly colour attitudes—mirroring findings by Zhou (2011) on tele-consultations and by Liu et al. (2023) on AI-driven wellness coaching. Thus, designers who foreground outcome-centric value propositions are more likely to foster early enthusiasm. Self-efficacy emerged as another decisive lever. Rooted in Bandura's social-cognitive theory (1997), the construct captures a user's conviction that "I can master this app if I try." Our results align with Chao (2019), who reported that older adults' confidence in basic smartphone skills directly lifted their openness to digital pharmacies. Elevated self-efficacy dampens technophobia, reduces dropout during onboarding, and ultimately cultivates a more favourable outlook toward continued use. Of all antecedents, perceived effectiveness (PE) exerted the greatest weight on attitude. This variable reflects outcome expectancy—users' belief that engaging with the app will tangibly improve their health status. Prior work has underscored its salience: Tajudeen et al. (2022) linked high PE perceptions to persistent engagement in diabetes-management apps, while Goel and Taneja (2023) found that PE eclipsed both PEOU and PU in predicting retention among fitness-tracker users. Our findings reinforce the idea that, in a domain where stakes are literally life-and-health, expected efficacy trumps convenience.

Downstream, attitude significantly shaped adoption intention, echoing the Theory of Reasoned Action (Ajzen & Fishbein, 1980) and later TAM extensions (Venkatesh et al., 2003). Although the standardized path coefficient was more modest than those feeding into attitude, its statistical strength confirms attitude's role as a mediating pivot between cognitive assessments and behavioural resolve. Model diagnostics buttress these insights. The structural equation explains 58.6 % of the variance in attitude and 42.8 % in intention—figures that compare favourably with past mHealth TAM replications. Stone–Geisser Q^2 values exceeded zero, evidencing predictive relevance, while all inner-VIF statistics stayed below the 3.3 threshold, ruling out harmful multicollinearity. Together, these metrics validate the decision to extend classical TAM with self-efficacy and perceived effectiveness, yielding a richer explanatory lens tailored to healthcare technology.

In sum, analysis highlights four practical imperatives: (1) craft interfaces that feel instantly familiar; (2) articulate concrete health gains, not abstract features; (3) embed scaffolding that nurtures user confidence (e.g., step-by-step tutorials, peer support); and (4) rigorously substantiate perceived effectiveness through evidence-based functionalities. Addressing these fronts simultaneously is likely to accelerate both positive attitudes and real-world uptake of mHealth solutions.

IMPLICATIONS

The study provides a deeper understanding of how various cognitive and psychological constructs influence user attitudes and their subsequent intention to adopt mobile health (mHealth) applications. The significant roles of perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness offer both theoretical advancement and actionable strategies for practice.

Theoretical implications

These results both confirm and extend the original Technology Acceptance Model (TAM; Davis, 1989). For mobile-health apps, the familiar drivers—perceived ease of use and perceived usefulness—still matter, yet they do not fully capture what shapes user attitudes. Adding self-efficacy and perceived effectiveness markedly boosts the model's explanatory power, showing that adoption decisions in healthcare hinge on more than usability and utility alone. In contexts where health outcomes are paramount, researchers should therefore enrich TAM with variables that tap users' psychological readiness and expectations of tangible benefits (Liu et al., 2023). The analysis also highlights self-efficacy—the belief that one can use the technology competently—as a particularly strong predictor of positive attitudes toward mHealth. This supports Bandura's (1997) Social Cognitive Theory, which emphasizes the importance of individual agency in behavioral outcomes. Its significance in the mHealth context indicates that future theoretical models should consistently include self-efficacy when investigating digital health behaviors. The results substantiate the mediating role of attitude between user beliefs and behavioral intention, aligning with the Theory of Reasoned Action (Ajzen & Fishbein, 1980). This indicates that attitudes are not merely outcomes but serve as essential intermediaries in converting perceptions (such as ease of use or effectiveness) into actual intent to use. Researchers exploring technology use behavior in healthcare or other emerging sectors should consider this mediating mechanism. The model's explanatory power, reflected its robustness. This supports the model as a theoretically grounded yet practically meaningful framework for analyzing user acceptance of digital health technologies, especially in under-researched or evolving contexts.

Practical implications

Since perceived ease of use significantly impacts attitude, mHealth developers must ensure that interfaces are clean, navigation is logical, and onboarding is smooth. Features such as voice input, simplified layouts, and language localization can help users with varying digital literacy levels engage effectively with the app. The influence of perceived usefulness suggests that users need to see clear, value-added benefits. Marketing materials, in-app notifications, and product descriptions should clearly communicate how the app supports users in managing conditions (e.g., medication reminders, symptom tracking) or improves their healthcare experience. Adding evidence from clinical trials, user testimonials, or integration with real-world outcomes can enhance trust. The significant effect of self-efficacy implies that simply offering a useful app is not enough—users must feel capable of using it. Developers and healthcare providers should offer user guides, video tutorials, FAQs, and in-app support to increase user confidence, particularly for elderly or non-tech-savvy populations. Public health initiatives can also include digital literacy training sessions to address this gap. As perceived effectiveness had the strongest influence on attitude, it is vital that users are convinced the app will yield real health benefits. This can be achieved by integrating progress tracking features, providing regular health insights, and visualizing improvements (e.g., reduced blood pressure, improved sleep) in simple, motivating formats. Policymakers can support mHealth adoption by funding awareness campaigns, ensuring internet connectivity in rural areas, and providing incentives for digital health usage. Additionally, integrating mHealth apps into public healthcare systems or insurance platforms can promote credibility and widespread adoption. Policies should also ensure data privacy and compliance to build user trust. Insights from this model can inform segment-specific strategies.

CONCLUSION

These findings deepen insight into mobile-health uptake by empirically testing an augmented Technology Acceptance

Model. The analysis shows that perceived ease of use, perceived usefulness, self-efficacy, and perceived effectiveness all foster a positive attitude toward mHealth, and that this attitude, in turn, strengthens the intention to adopt. Perceived effectiveness exerts the greatest influence, underscoring how strongly users weigh expected health outcomes when evaluating such apps. The extended model explains a considerable share of the variance in both attitude and behavioural intention, attesting to its robustness in digital-health settings.

Adding self-efficacy and outcome expectancies to the classic TAM enables the framework to capture both cognitive judgements and motivational beliefs that shape mHealth behaviour. Theoretically, the work broadens technology-adoption scholarship by validating a multi-factor structure that positions psychological confidence and outcome assessment alongside traditional TAM drivers. Practically, the findings encourage developers and health-sector policymakers to create mHealth solutions that are intuitive, visibly beneficial, and supportive. Interfaces should minimise user effort, demonstrate measurable health gains, and build confidence through clear guidance and training. Overall, the study pinpoints the key levers of mHealth adoption and invites future research to examine demographic, cultural, and contextual moderators, paving the way for more inclusive and effective mobile-health interventions.

REFERENCES

i. Addotey-Delove, M., Scott, R. E., & Mars, M. (2022). A healthcare workers' mHealth adoption instrument for the devel oping world. BMC Health Services Research, 22(1), 1225. https://doi.org/10.1186/s12913-022-08592-0

ii. Agarwal, S., Rana, M. S., & Sharma, P. (2023). The health impact of mHealth interventions in India: A systematic re view. Online Journal of Public Health Informatics, 15, e50927. https://doi.org/10.2196/5092

iii. Ajzen, I., & Fishbein, M. (1980). Understanding attitudes and predicting social behavior. Prentice-Hall.

iv. Alam, M. M. D., Alam, M. Z., Rahman, S. A., & Taghizadeh, S. K. (2021). Factors influencing mHealth adoption and its impact on mental wellbeing during COVID-19 pandemic: A SEM-ANN approach. Journal of Biomedical Informatics, 116, 103722. https://doi.org/10.1016/j.jbi.2021.103722

v. Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

vi. Black, J., & Cherrington, J. (2022). Posthuman to Inhuman: mHealth Technologies and the Digital Health Assem blage. Theory & Event, 25, 726. https://doi.org/10.1353/tae.2022.0039

vii. Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and exten sion of the UTAUT model. Frontiers in Psychology, 10, 1652. https://doi.org/10.3389/fpsyg.2019.01652

viii. Chiu, W., Won, D., & Chen, J. (2025). Older adults' adoption behavior of mobile health (mHealth) apps: Integrating technology readiness with protection motivation theory. Asia Pacific Journal of Marketing and Logistics. Advance online publication. https://doi.org/10.1108/APJML-10-2024-1468

ix. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

x. Deng, H., Zhang, J., & Chen, H. (2024). Quality factors affecting the continued use of mobile health apps in ethnic minority regions of Southwest China using PLS-SEM and ANN. Scientific Reports, 14(1), 25469. https://doi.org/10.1038/s41598-024-75410-4

xi. DeSouza, S. I., Rashmi, M. R., Vasanthi, A. P., Joseph, S. M., & Rodrigues, R. (2014). Mobile phones: The next step towards healthcare delivery in rural India? PLOS ONE, 9(8), e104895. https://doi.org/10.1371/journal.pone.0104895

xii. Fan, S., Jain, R. C., & Kankanhalli, M. S. (2023). A comprehensive picture of factors affecting user willingness to use mobile health applications (arXiv Preprint No. 2305.05962). arXiv.

https://arxiv.org/abs/2305.05962

xiii. Ferreira, J. B., & Caldeira, T. A. (2024). MT48 Enhanced Healthcare Through the Adoption of Mobile Health Apps. Value in Health.

xiv. Garavand, A., Samadbeik, M., Nadri, H., Rahimi, B., & Asadi, H. (2019). Effective factors in adoption of mobile health applications between medical sciences students: Application of the UTAUT model. Methods of Information in Medicine, 58(4-5), 131–139. https://doi.org/10.1055/s-0040-1701607

xv. Goel, A., & Taneja, A. (2023). User motivation and adoption of mHealth services: A multi-group analysis of genera tional cohorts. Telematics and Informatics, 81, 102046. https://doi.org/10.1016/j.tele.2023.102046

xvi. Goel, A., & Taneja, U. (2023). Mobile health applications for health-care delivery: Trends, opportunities, and chal lenges. Journal of Public Health. https://doi.org/10.1007/s10389-023-02165-z

xvii. Guo, X., Han, X., Zhang, X., Dang, Y., & Chen, C. (2015). Investigating m-health acceptance from a Protection Motivation Theory perspective: Gender and age differences. Telemedicine and e-Health, 21(8), 661–669. https://doi. org/10.1089/tmj.2014.0166 pubmed.ncbi.nlm.nih.gov

xviii. Healthcare at Your Fingertips: Case of mHealth in India. | Centre For Civil Society. (n.d.). Retrieved May 20, 2024, from https://ccs.in/healthcare-your-fingertips-case-mhealth-india-0

xix. Huang, B., Estai, M., Schultz, E. C., & Shenouda, M. (2025). Perspectives of Front-Line Clinicians and Remote Re viewers on Smartphone-Based Photography for Assessing Traumatic Dental Injuries: A Qualitative Study. University of Minnesota Digital Conservancy.

xx. India: Mobile phone internet users 2050 | Statista. (n.d.). Retrieved May 20, 2024, from https://www.statista.com/ statistics/558610/number-of-mobile-internet-user-in-india/

xxi. Liang, H., & Xue, Y. (Lucky). (2010). Understanding Security Behaviors in Personal Computer Usage: A Threat Avoidance Perspective. Journal of the Association for Information Systems, 11(7). https://doiorg/10.17705/1jais.00232

xxii. Liu, J. Y. W., Liu, Y., & Lee, K. T. (2023). Determinants of intention to continue mHealth services in chronic disease management: Extending TAM with perceived trust and health literacy. Technological Forecasting and Social Change, 187, 122299. https://doi.org/10.1016/j.techfore.2022.122299

xxiii. Liu, J. Y. W., Liu, Y., & Lee, K. T. (2023). Determinants of intention to continue mHealth services in chronic disease management: Extending TAM with perceived trust and health literacy. Technological Forecasting and Social Change, 187, 122299. https://doi.org/10.1016/j.techfore.2022.122299

xxiv. Mouloudj, K., Bouarar, A. C., Martínez Asanza, D., Saadaoui, L., Mouloudj, S., Njoku, A. U., Evans, M. A., & Bouarar, A. (2023). Factors influencing the adoption of digital health apps: An extended Technology Acceptance Model (TAM). In Integrating digital health strategies for effective administration (pp. 116–132). IGI Global. https://doi.org/10.4018/978-1-6684-8337-4.ch007

xxv. Palas, J. U., Sorwar, G., Hoque, M. R., & Sivabalan, A. (2022). Factors influencing the elderly's adoption of mHealth: An empirical study using an extended UTAUT2 model. BMC Medical Informatics and Decision Making, 22(1), 191. https://doi.org/10.1186/s12911-022-01917-3 pubmed.ncbi.nlm.nih.gov

xxvi. PricewaterhouseCoopers. (n.d.). mHealth and the Healthcare industry. PwC. Retrieved May 20, 2024, from https:// www.pwc.in/press-releases/2017/mhealth-expected-to-be-crucial-in-making-healthcare-accessible-in-india-pwc-cii-paper.html

xxvii. Rahman, A., & Uddin, J. (2025). Revealing factors influencing mHealth adoption intention among Generation Y: An empirical study using SEM-ANN-IPMA analysis. Digital, 5(2), 9. https://doi.org/10.3390/digital5020009

xxviii. Rajak, M., & Shaw, K. (2021). An extension of technology acceptance model for mHealth user adoption. Technology in Society, 67, 101800. https://doi.org/10.1016/j.techsoc.2021.101800

xxix. Riley, W. T., Rivera, D. E., Atienza, A. A., Nilsen, W., Allison, S. M., & Mermelstein, R. (2011). Health behavior models in the age of mobile interventions: Are our theories up to the task? Translational Behavioral Medicine, 1(1), 53–71. https://doi.org/10.1007/s13142-011-0021-7

xxx. Silva, P. (2015). Davis' Technology Acceptance Model (TAM) (1989). In Information Seeking Behavior and Technology Adoption: Theories and Trends (pp. 205–219). IGI Global. https://doi.org/10.4018/978-1-4666-8156-9.ch013

xxxi. Swain, S., Muduli, K., Kumar, A., & Luthra, S. (2023). Analysis of barriers of mHealth adoption in the context of sustainable operational practices in health care supply chains. International Journal of Industrial Engineering and Operations Management, 6(2), 85–116. https://doi.org/10.1108/IJIEOM-12-2022-0067

xxxii. Tajudeen, F. P., Bahar, N., Maw Pin, T., & Saedon, N. I. (2022). Mobile Technologies and Healthy Ageing: A Bibliometric Analysis on Publication Trends and Knowledge Structure of mHealth Research for Older Adults. International Journal of Human–Computer Interaction, 38(2), 118–130. https://doi.org/10.1080/10447318.2021.1926115

xxxiii. Tian, X. F., & Wu, R. Z. (2022). Determinants of the mobile health continuance intention of elders with chronic diseases: An integrated framework of ECM-ISC and UTAUT. International Journal of Environmental Research and Public Health, 19(16), 9980. https://doi.org/10.3390/ijerph19169980

xxxiv. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

xxxv. Weichelt, B. P., Burke, R., Kieke, B., Pilz, M., & Shimpi, N. (2024). Provider adoption of mHealth in rural patient care: Web-based survey study. JMIR Human Factors, 11, e55443. https://doi.org/10.2196/55443

xxxvi. Yang, M., Al Mamun, A., Gao, J., Rahman, M. K., Salameh, A. A., & Alam, S. S. (2024). Predicting m-health acceptance from the perspective of the unified theory of acceptance and use of technology. Scientific Reports, 14(1), 339. https://doi.org/10.1038/s41598-023-50436-2 pubmed.ncbi.nlm.nih.gov

xxxvii. Zhou, T. (2011). Understanding mobile Internet continuance usage from the perspectives of UTAUT and flow. Information Development, 27(3), 207–218. https://doi.org/10.1177/0266666911414596

Herding in Factor Portfolios: A Regime-Switching Perspective on the Indian Market

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ABSTRACT

The current research investigated dynamic herd behavior in different factor portfolios for the Indian Stock Market. The study is conducted on three factors: market size, volume and profit-book ratio from 2009-2023. Using the three-regime Markov model, the study documented notable results. We observed herding for large, high-volume, and value stocks with extremely high volatile regimes. These results exhibit that the type of stocks matters while investing in the stock markets. Investors behave differently for various types of stocks and impact the market trend, especially in times of unprecedented situations. These results have implications for investors, market regulators, and portfolio managers.

KEYWORDS

Herd behavior, Markov Regime Switching model, Volatility, Market Size, Volume, Value/Growth Stocks

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INTRODUCTION

In past years, behavioral finance has become the most interesting research domain for researchers. Behavioral finance entails market inefficiency and irrationality against the efficient market hypothesis (Sharma & Kumar, 2020). Investors react irrationally because of various behavioral biases like recency bias, overconfidence bias, loss aversion bias and herd behavior, etc. Investors start acting irrationally because of these anomalies, leading to stock market bubbles, high market fluctuations, and momentum in the stock market (Kapoor & Prosad, 2017). Herding is one of the most common and observed biases in the financial market, where investors imitate the actions of similar types of investors, leading to trends in market prices. There are many causes behind herd behavior, which can be deduced from a theoretical framework. Numerous prior studies have elucidated the emergence of herding behavior, highlighting several key contributing factors. These include reputational concerns, the phenomenon of informational cascades, the superiority of certain information, and the complexities inherent in the informational structure of the environment. (Avery & Zemsky, 1998; Bikhchandani et al., 1992; Scharfstein & Stein, 1990). Studying herding behavior is crucial as it can lead to volatility in the market, widening the disparity between the market price and the intrinsic value of any stock, and potentially leading to a bubble-like scenario in the financial markets (Bikhchandani et al., 1992; Chiang & Zheng, 2010). Hence, it is vital to explore similarities among the trading behavior of Indian investors.

An understanding of the herd behavior encourages better investment decisions with portfolio diversification. So, with this objective, we examine dynamic herding in the Indian stock market from January 2009 to March 2023. Time-varying herding refers to the phenomenon of investors showing patterns of imitations, and these patterns change according to time. The ever-changing aspect of herding will shift when new information enters the market, superseding outdated information. There are several reasons for selecting the Indian stock market. To begin with, emerging economies such as India exhibit herding behavior due to cultural variances, inadequate enforcement of laws, and investors who are uneducated and uninformed.(Chang et al., 2000; Kanojia et al., 2022; Lao & Singh, 2011). Next, India is a rapidly growing economy among emerging markets, characterized by increasingly relaxed regulations on foreign investment. This has resulted in a significant influx of Foreign Institutional Investment (FII) into the country. Consequently, it has been noted that during periods of high market volatility, investors tend to mirror the actions of FIIs and align their movements accordingly. This study contributes various insights to the body of literature on herding behavior. To begin with, the current research utilized a Regime Switching constant probability model, incorporating three Markov states, to analyze the Indian stock market for the presence of herd behavior. The three-regime model allows for the exploration of the dynamic characteristics of cross-sectional dispersion and the impact of various structural breaks or events on the migration of the data into different regimes or states where herd behavior can be detected (Balcilar et al., 2013). Firstly, there has been limited research that examines the important autocorrelation feature of cross-sectional absolute deviation within a time-varying framework, and this research incorporates two lagged terms of the explained variable in the Regime model. In this analysis, we investigate the significant influence of volatility on herding behavior in three different portfolios.

This research is specifically focused on studying dynamic herding in different factor portfolios. We have examined dynamic herding in three factors i.e.: size, volume, and book-to-profit ratio. For bifurcating the sample into different portfolios, we have applied the methodology of Fama and French (2015).

The investigation of time-varying herding has implications for policymakers and market participants by helping them identify the potential market risk associated with the presence of herding. Moreover, strategies can be formed based on identifying dynamic herding to maintain financial stability and market efficiency. The structure of the paper is as follows: Section 2 includes the relevant previous research. The empirical framework is outlined in Section 3. Section 4 analyzes the findings and interpretations, while Section 5 provides the concluding observations and recommendations for the study.

REVIEW OF LITERATURE

This section provides a detailed review of previous studies that showed the existence or absence of Herd Behavior in the Financial Market.

2.1 Herding in the Financial Market

Herd Behavior is a biasness that makes the investors irrational and prone to risk. Hence, it is necessary to estimate the herding in the financial market. Literature depicts two strands of literature that estimate uniformity in the equity market. One strand of literature is related to measuring herding among individual market participants like individual investors, institutional investors, etc. This type of herding can be measured using a model devised by Lakonishok et al. (1992). While another strand measured herding in the whole market using the cross-sectional standard and absolute deviation. This model was developed by Christie and Huang (1995) and later on modified by Chang et al. (2000) who stated the linear and positive relationship between absolute market return and dispersion but this relationship becomes nonlinear and negative at the time of crowd behavior.

Many empirical studies have investigated herding us-

ing the cross-sectional absolute dispersion. Gleason et al. (2004) conducted a study on herd behavior by analyzing intraday data from sector-specific exchange-traded funds during periods of extreme volatility in the American stock exchange. Their findings shed light on how investors often act collectively, particularly in turbulent market conditions. They applied both cross-sectional standard deviation and absolute deviation. Results exhibited insignificant herding in sectoral ETFs. Tan et al. (2008) explored the phenomenon of herd behavior within the context of Chinese A and B shares, which are traded on the Shanghai and Shenzhen stock exchanges. Utilizing the cross-sectional absolute deviation (CSAD) method, they aimed to analyze how investors' collective actions influenced stock market trends and prices, highlighting the dynamics of investor sentiment in these Chinese markets. Overall results exhibited daily herding in both the A-share and B-share markets, while weaker evidences of herding are found for monthly and weekly data. Moreover, asymmetries in herd behavior are also examined based on market returns, volume, and volatility. Evidence of significant herding is found during rising market returns, high volume, and higher volatility periods in all the markets. However, herding is stronger in the Shanghai A-share market as compared to the B-share market. Benkraiem et al. (2019) checked out herding in listed SMEs in French and UK equity markets for the period 2005-2016. Results revealed that uniformity is stronger in micro-cap in both the markets as compared to the large-cap. It depicts small-cap companies exhibiting a higher intensity of herding as compared to large-cap companies. Choi and Yoon (2020) detected uniformity in the Korean KOSDAQ and KOSPI markets using Quantile regression and a linear approach. The analysis utilized a daily series of the data spanning from 2003 to 2018. Results showed herding in the down market according to the CSAD approach while quantile regression results reveal significant herding in upper and lower quantiles. They also noted evidence of negative herding using a quantile regression approach. This indicates that herding is the phenomenon of extreme market conditions. Investors react quickly during these uncertain situations.

Similarly, Benkraiem et al. (2021) examined uniform behavior in the French and UK by incorporating a linear approach. The study relates herding between listed small and medium enterprises and large stock companies. Results exhibit herding in small-cap companies in the tranquil period as compared to no herding in the uncertain period. Kanojia et al., (2022) have studied static herding in the Indian stock market for the time spanning from 2009 to 2018 exhibiting insignificant herding among Indian market participants.

The literature reveals that numerous studies have employed the linear regression method to scrutinize herding behavior, yielding mixed results regarding its presence or absence in financial stock markets; later on, the studies shifted their focus toward identifying the dynamic nature of herding. Hwang and Salmon (2004) first explored a model for identifying dynamic herding by deploying Kalman's filter state space model. They argued that betas can change over time and proposed a time-varying model to measure herding using monthly betas. The proposed model is tested on two countries, namely the US and South Korea, showing evidence of significant herding during normal periods. The research showed that the market began to exhibit efficiency during times of crisis. Herding is typically a temporary occurrence assessed through daily or intraday data, as it tends to arise in extreme market conditions (Gleason et al., 2004). By keeping in mind the short-term presence of herding, Klein (2013) identified the time-varying herding using the Markov switching model by bifurcating the market into two regimes, namely turmoil and tranquil regimes. They analyzed herding in European and the US markets from 2001-2011. The findings of the study reflect uniform trading in both markets during turmoil regimes as compared to tranquil regimes. Balcilar et al. (2013) also examined dynamic herding in the Gulf countries by utilizing the Markov model. Their research revealed three distinct market regimes: low, high, and crash regimes. The study's findings indicate that herding occurs in the crash regime, highlighting its presence during extreme market movements.

Similarly, researchers have examined the importance of exploring dynamic herding and many studies further scrutinize dynamic herding in different financial markets. like Babalos et al (2015) studied crowd behavior in the real estate markets in the US by using a regime model. They evidenced the presence of herding during the crash regime as compared to no herding in the static model. Later on a study by Bohl et al. (2016) observe that many studies have ignored the time-varying concept in transition probabilities while estimating dynamic herding using the regime model. In a highly volatile regime, anti-herding in the US stock market reveals that investors focus on fundamentals rather than following the crowd during extreme movements. This suggests a more rational approach to navigating market fluctuations. Similarly, Stavroyiannis and Babalos (2020) also inspected the herding coefficients in the Eurozone stock market but with a time-varying effect. They have also considered stochastic volatility to be time-varying. The study's results indicated the presence of anti-herding, also known as negative herding.

Fu and Wu (2021) investigated herd formation in the Chinese equity market by deploying the Markov model. In the Chinese market, researchers discovered two distinct regimes: a high volatile regime and a low-volatile regime. Their findings demonstrated that herd behavior thrives in the highly volatile landscape, while adverse herding emerges in the calmer, low-volatility regime. This insight highlights the crucial dynamics at play in market behavior, offering valuable implications for investors and traders alike. Results also indicated a stronger level of herding for large-cap stocks, value stocks, and high trading volume. Mand and Sifat (2021) detected significant evidence of herd formation in Malaysia using a regime model in

the highly volatile regime. The studies indicate that herding behavior tends to exaggerate significantly during periods of uncertainty in the majority of financial markets. This suggests that market participants are more likely to follow the crowd when uncertainty is elevated, making it crucial for investors to be aware of this tendency. In a similar manner, Yamaka et al. (2021) explore herding in the Japanese stock market using both CSAD and Markov switching approaches. They divided the market into two regimes, specifically the up and down-market regimes. They provided evidence for significant herding in the up-market regime against no herding in the down-market regime. The paper of Yang and Chuang (2023) studied the time-varying herding in the US, China, and Taiwan stock markets during various events. The results of their study mention the evidence of anti-herding in all the chosen stock markets after 2010. They also found the existence of different herding states through their proposed model. Likewise, the recent study of Javaira et al. (2024) investigated the dynamic herding and volatility relationship during COVID-19 in developed countries. Their study employed the Markov regime switching model and found that investors switch from anti-herding to herding-like situations at the time of unprecedented crises. The study of Rubbaniy et al. (2025) tested the various dynamics in energy stock markets. They used the state space model and quantile on quantile regression models to test fundamental and intentional herding. Findings elaborate on the evidence of intentional herding in North American energy stocks.

2.2 Indian-specific Evidence on Herding

There exists a substantial body of works regarding herding behavior in the Indian stock market, which presents a range of findings that indicate both the presence and absence of such behavior. Many studies have used static models to analyze herding among Indian market participants. Lao and Singh (2011) analyzed the herding behavior in the Chinese and Indian stock markets from 1999 to 2009 through the CSAD approach, revealing crucial trends and insights that can inform future investment strategies. The results from various studies demonstrate herding behavior in stock markets, with particularly greater intensity noted in the Chinese stock market. Garg and Gulati (2013) conducted an analysis of herding behavior in the Indian share market using a comprehensive dataset encompassing daily, monthly, and weekly data from the National Stock Exchange spanning from 2000 to 2013. The findings indicate that there is a notable absence of herding behavior in the Indian stock market, even in uncertain situations, such as significant fluctuations in trading volume and market trends. Building on this, Poshakwale and Mandal (2014) employed the Kalman filter methodology to further investigate herding in the Indian financial market. Their study incorporated time-varying state variables, including market volatility and directional trends, and highlighted significant evidence of herd instinct, particularly during bear market conditions. Furthermore, Kumar et al. (2016) documented no herding among Indian stock market participants during the bull and bear phases as well as under extreme market conditions. It conveys that investors in the Indian market tend to rely on the fundamental analysis of companies rather than succumbing to the influence of market events. Supporting this perspective, Ganesh et al. (2017) analyzed uniform behavior in the Indian stock markets from 2005 to 2015 and concluded that herding behavior was largely absent, with notable exceptions in the years 2011 and 2014. Collectively, the above results contribute to the understanding of behavioral dynamics in emerging markets and their implications for investment strategies. Recently, the study of Ansari and Ansari (2021) measured herding for the period 207-2018 using the static model in normal and bull/bear phases. Their findings showed the anti-herding in Indian market in all market conditions. Similarly, the study conducted by Kanojia et al. (2022) reveals no herd formation within the Indian capital market, as evidenced by the application of the CSAD methodology over the period from 2009 to 2018. The findings indicate a consistent absence of herding across varying market conditions. This comprehensive literature review highlights that a majority of scholarly analyses about the Indian market have demonstrated a lack of herding tendencies when employing static models. Collectively, these studies suggest that the Indian stock market operates with a degree of efficiency, where investors are inclined to make rational and informed decisions.

2.3 Research Gap

The examination of literature indicates that the Indian market presents conflicting evidence regarding the existence of herding. The existing researches has employed a static method to assess herding, primarily focusing on the analysis of herding during rising or falling market conditions. Despite the significant advancements in regulatory frameworks for investment following the liberalization of the Indian market, India remains an emerging economy characterized by a substantial population of small retail investors. These investors often exhibit irrational behaviors during periods of extreme market volatility, complicating investment dynamics and overall market stability. (Ansari & Ansari, 2021). Additionally, in the past decade, the Indian stock market has seen an increased participation of foreign institutional investors, which has made it susceptible to different investor emotions such as herd behavior and positive feedback trading (Mukherjee & Tiwari, 2022). Furthermore, the arrival of extraordinary occurrences such as COVID-19 has greatly amplified inefficiencies in the Indian stock market (Bhatia, 2022). As a result, domestic investors increasingly mirrored the actions of foreign investors, illustrating the ripple effect of global market dynamics. All these above-mentioned reasons make the study useful to explore whether, with time, herding behavior has evolved in the Indian market or vanished. The present research is unlike the recent study of Ansari and Ansari (2021) in several ways. First, they tested herding in the up/

down market, but we have analyzed herding with special reference to volatility. First, they applied the static model to assess herding, whereas we investigate the time-varying herding within a three-regime framework. Although the of Poshakwale and Mandal (2014) explored herd mentality by applying the Kalman filter witstudy hin the National Stock Exchange of India, utilizing monthly beta instead of daily or intraday data. The study of Kabir and Shakur (2018) investigated the consistency in both high and low-volatile regimes across various countries, including India, utilizing the Smooth transition model. However, this study is different from their study in the methodological framework by incorporating three regime specifications using the Markov regime-switching model. This study investigates herding behavior across various factor portfolios, including size, volume, and book-to-market ratio.

RESEARCH METHODOLOGY

It describes the methodology adopted to test the herding and Herding Intensity in the Indian Stock Market. First, the data is collected from the Prowess IQ database. Then, data filtration is performed using the linear interpolation method to replace the missing values. After that, the dependent variable, i.e., Market Return, is calculated by taking an equal-weighted average of the daily logged values of individual stock market returns on a day t of all companies listed in the S & P BSE 500 index. Then, the dependent variable, i.e., Cross-sectional Absolute Deviation, is calculated. In the next step, a linear OLS regression is performed on the time series variables using E-view 9.0. To evaluate the dynamic herding from 2009 to 2023, the Markov Regime switching model is employed. However, prior to that, non-linearity is examined within the model. Then, the number of Regimes is identified using various criteria. Herding is tested for different factor portfolios, like Large/Small-cap stocks, value/Growth stocks, and high/low volume stocks, using the regime model. The work of Fama and French (1995, 2015) has been used for bifurcating different stocks into different portfolios. A detailed explanation of data and the econometric framework is provided in the various sub-sections.

3.1 Data

This section explains the data and their properties used in the study, which will guide the analytical work of the study.

3.1.1 Sources of data

This study examines herd behavior within the overall market and across various market portfolios, specifically focusing on size portfolios, volume-based portfolios, and price-to-book ratios. The dataset consists of daily adjusted closing prices, annual market capitalization, yearly price-to-book ratios, and the annual number of shares traded by companies listed in the S&P BSE 500. The S&P BSE 500 serves as a significant index representing all 20 large industries within the economy. As a market capitalization-weighted index, it accounts for approximately 93% of the total market size of the Bombay Stock Exchange (BSE) (www.moneycontol.com, 2021). Daily data may be regarded as high-frequency data in certain situations since it offers greater accuracy than weekly or monthly data (Hung, 2019; Jebran & Iqbal, 2016). When using weekly or monthly data, valuable information can be lost since it averages out daily fluctuations. While numerous studies have treated intraday data as high-frequency due to constraints related to time and data availability, this research regards daily data as the next best option to high-frequency data, as it can illustrate volatility more distinctly than lower-frequency data. The information utilized in this study was sourced from the Prowess IQ database, provided by the Centre for Monitoring Indian Economy (CMIE). The companies that have missing values of more than 10 per cent of the total number of observations, are also excluded. Furthermore, for the companies that have missing values of less than 10 per cent, data for those companies are replaced using linear interpolation (Mertler et al., 2021). Linear interpolation is a type of imputation technique that replaces the missing values linearly in increasing order. This research applied linear interpolation instead of the average value method because the mean method provides a large number of errors as related to the mean value method (Noor et al., 2015). In the evaluation of herding behavior across different portfolios, the number of companies involved in the study varies. For the market-cap and volume-based portfolios, a total of 337 companies have been analyzed, those companies are excluded from the study that have not traded from the beginning to end of the study period i.e., 2009-2023. Companies lacking yearly September data on volume and market capitalization are excluded from this portion of the analysis. In contrast, the price-to-book ratio portfolio consists of 320 companies. Within this portfolio, companies not having march data related to price-to-book ratio are omitted from consideration. Furthermore, companies demonstrating negative book values are eliminated from the price-to-book ratio portfolio analysis Fama and French (1995). The criteria for making a single sorted portfolio are taken from the study of Fama & French (1995, 1996). For analytical work, we have used E-views 9.0, MS-Excel, R, SPSS 25 and Ox-metrics 7.0.

3.1.2 Period of the study

The study collected data for almost 15 years from January 2009 to March 2023. The reason for selecting this study period is that it encompasses many crucial events and impacts that might affect the Indian economy.

3.2 Econometric Framework

This section describes the econometrics models used to investigate herding in the Indian stock market.

Static Measure

The static measure pertains to the analysis of linear market-wide herding phenomena. The model established by Christie and Huang (1995) posits that at extreme market movements or heightened market stress, distinct stakeholders are prone to subordinating their independent opinions in favor of prevailing market consensus. This behavior results in a convergence of actions among investors, creating a herd-like formation. Consequently, this herding behavior affects market dynamics, where individual stock returns become increasingly aligned with aggregate market returns, leading to a reduction in dispersion. Christie and Huang make a cross-sectional standard deviation as a metric for quantifying uniform behavior during periods of uncertainty, with the dispersion calculation being delineated as follows:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} \frac{\left(R_{i,t} - R_{m,t}\right)^2}{(N-1)}} \quad (1)$$

$CSSD_t$ is the cross-sectional standard deviation. $R_{i,t}$ is the individual stock returns on a day t, $R_{m,t}$ is the cross-sectional average of stock returns on a day t. N is the total number of firms on a day t. The Study calculated equal weighted market return instead of market-cap weighted market return because, from our analysis, we detected that Indian companies yield similar results in both cases for large samples. The research utilized a market return proxy that assigned equal weights to every stock in the portfolio, which has also been calculated by various studies (Chang et al., 2000; Chiang & Zheng, 2010; Garg & Gulati, 2013; Kanojia et al., 2022). That is why, we did not calculate market-cap weighted market return. If dispersion is lower, then it depicts anti-herding. In share market analysis, a diminished dispersion in asset returns may suggest the presence of crowd behavior among stakeholders. Nevertheless, it is crucial to note that lower dispersion does not automatically imply herding is occurring. During an uncertain period, the rational asset pricing model posits that individual stock returns react with varying sensitivities to the prevailing market environment. This disparity in sensitivity tends to amplify dispersion, reflecting the diverse responses of market participants and reinforcing the notion of potential deviations from fundamental valuations. But at the time of herd behavior, this dispersion starts decreasing. They tested herding during market stress using the following regression model:

$$CSSD_t = \alpha + \beta_t^{dn} D_t^{dn} + \beta_t^{up} D_t^{up} + \varepsilon_t \quad (2)$$

D_t^{dn} is the dummy variable at a time t when the market return is in the extreme lower tails of the distribution. D_t^{up} is the dummy variable at a time t when the market return is in the extreme upper tail of the distribution. In the presence of herd behavior, the coefficients β_t^{dn} and β_t^{up} is become negative. To define the upper and lower tail, CH used the 1 and 5 per cent criteria of the total number of observations. Subsequently, the CH (Christie and Huang) model was refined by Chang et al. (2000), who posited that the traditional rational asset pricing model not only characterizes a positive association between market return dispersion and absolute market return but that this relationship also follows a linear trajectory. However, in scenarios where herd behavior is present, this relationship becomes both decreasing and non-linear. They originated a model grounded in the capital asset pricing framework that delineates an increasing and linear relationship between cross-sectional absolute deviation (CSAD) and market return. They introduced a non-linear term within the regression model to identify the effects of herding behavior and concluded that CSAD tends to increase at a diminishing rate or decrease when herding is significant. The methodology for calculating CSAD along with the model specification is outlined as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right| \quad (3)$$

In this context, CSAD (Cross-Sectional Absolute Deviation) is defined as dispersion's measure of individual stock returns. It is analyzed as the absolute deviation of individual stock returns from the equally weighted cross-sectional average of n returns at time t. N represents the number of firms considered at time t.

$$CSAD_t = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \left(R_{m,t} \right)^2 + \varepsilon_t \quad (4)$$

The above regression model is a basic model used to test the herding in normal situations for all stocks. $| R_{m,t} |$ is the absolute market return, and $(R_{m,t})^2$ is the squared market return. The increasing and linear relationship can be established through the positive coefficient 1. During periods of herding, the association among the variables transitions to a non-linear and negative correlation, resulting in a significantly negative coefficient. the coefficient 2 becomes significantly negative.

We have used the above regression model with some modifications to examine the presence or absence of herding. Our model is as follows:

$$CSAD_t = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \left(R_{m,t} - \overline{R}_m \right)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \varepsilon_t \quad (5)$$

The presence of absolute market return and squared market return in the same model leads to a high level of multicollinearity, which needs to be addressed in the OLS models. To address the issue of multicollinearity, we refer to the research conducted by Yao et al. (2014), which starts

by determining the squared deviation of market returns by taking the difference between the actual market returns and their mean. Furthermore, the research incorporates a two-lag term for the dispersion variable within the model to effectively account for the substantial autocorrelation properties observed in dispersion data. The decision to include only two lag terms is based on empirical observations indicating that higher-order lag terms do not enhance the robustness of the results (Lao & Singh, 2011). Many empirical studies included lag terms in their model to remove the autocorrelation. The analysis employed standard errors that are consistent with heteroscedasticity and autocorrelation, following the methodology established by Newey and West (1987). Additionally, a lag term of the response variable was incorporated to accurately estimate the regression coefficients

- **Non-linearity Test**

In interpreting the results, if the critical value is higher than the test statistic, we fail to reject the null hypothesis, suggesting non-stationarity in the series. Conversely, if the test statistic exceeds the critical value, we reject the null hypothesis, concluding stationarity in the data.

- **Likelihood Ratio Test**

It involves testing whether the maximized log-likelihood function is falling sharply after imposing non-linear restrictions on data. It includes the following steps:

1. Calculating maximized log-likelihood for both constrained and unconstrained models. Note that the likelihood value for the unconstrained model is always at least greater or equal to the restricted model (Brooks, 2008).

2. After that we have calculated the likelihood ratio statistic using the formula as per equation (6)

$$LR = -2(L_r - L_u) \sim x^2(m) \qquad (6)$$

Here, m is number of restrictions

3. In the Regime model, there is an incidence of unidentified nuisance parameters under the null hypothesis (Brooks, 2008), hence standard distribution does not apply to the regime model.

So we have also reported the p-values calculated using the approximate upper bound test proposed by Davies (1987). This test is performed in R.

b. **Time-varying Measure**

In time series analysis, non-linear structures often preclude the practical application of linear models. These models fail to adequately capture important financial data characteristics, such as leptokurtosis, volatility clustering, and leverage effects (Brooks, 2008). A non-linear data generating process means the current series is related non-linearly to the current and previous value of the error term (Campbell et al., 1997). Various non-linear models have been developed to address these complexities, specifically focusing on non-linearities in either the mean or the variance. For instance, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models exhibit non-linearity in variance, while switching models adapt their behavior based on different time points, thereby accommodating the dynamic nature of financial markets.

- **Markov Regime Switching Model**

Sometimes, a change in financial time series is permanent or temporary. When there is a change in the behavior of a series at one time, and again, the series reverts to its original nature; this is called regime shift. Regime changes can be of two types: Markov regime shifts and threshold autoregressive models (Brooks, 2019).

In Markov regime models, there is a presence of m number of regimes or states based on the Markov Property. The Markov property asserts that the transition probability to any future state t+1 is determined solely by the current state at time t, without consideration of preceding states. This concept can be articulated mathematically as follows:

$$P(y_0, y_1, y_2 \ldots\ldots\ldots y_t) = P(y_{t+1} | y_t) \qquad (7)$$

In the Markov Regime model, regime-switching may occur at both the average and standard deviation of the error term. First Hamilton (1989) put forward an algorithm based on the discrete-state regime shifts in the Markov process. Hence this study also followed this approach and models herding using the Regime-Switching model.

Through formal testing, the study found three regimes in the Indian stock market by succeeding in the seminal work of Balcilar et al. (2013) and Fu and Wu (2021). Equation (2) is just extended by dividing the series into three regimes shifting across intercept and standard deviation as shown in equation 8. All the variables are varying across regimes except lags of the dependent variable.

$$CSAD_t = \gamma_{0,r_t} + \gamma_{1,r_t} \left| R_{m,t} \right| + \gamma_{2,r_t} \left(R_{m,t} - \overline{R}_m \right)^2 + \gamma_3 CSAD_{t-1} + \gamma_4 CSAD_{t-2} + \sigma_{r_t} \varepsilon_t \qquad (8)$$

Here, $\in t \sim N(0,1)$ is the innovation term and σ_{rt} is the standard deviation, a measure of volatility. r_t is discrete regime variable can take the values $r_t = [0,1,2,\ldots\ldots,m]$ by following the three-state first-order Markov process. The Markov

property is based on the transition probabilities which are constant across states and represented by the following specifications,

$$P\left(r_t = j\right) = p_{ij} \quad (9)$$

These transition probabilities with m number of regimes form a transition matrix of (m*m) regimes which is stated here as (Guo et al., 2011)

$$P = \left[p_{00}\, p_{01} \ldots\ldots\ldots p_{0m}\, p_{10}\, p_{11} \ldots\ldots\ldots p_{1m}\, p_{m0}\, p_{m1} \ldots\ldots\ldots p_{mm}\right] \quad (10)$$

$$\sum_{j=1}^{m} p_{ij} = 1 \text{ where } j = 0, 1, 2, \ldots\ldots, m \text{ and } 0 \leq p_{ij} \leq 1$$

Where pij is the constant transition probabilities in regime i at a time t+1 certain that the market was in regime j at t-1 time period. In the Markov model, expected duration is also calculated which states how many numbers of days, months, or years, the particular regime lasts for. It is calculated here as:

$$E\left(D_i\right) = \frac{1}{1-p_{ii}}, \; i = 1, 2, 3 \ldots\ldots\ldots m \quad (11)$$

Where, E(Di) denotes the duration of regime i.

The estimation method used for the regime model is the maximum likelihood and robust standard error is calculated using Hessian and OPG matrix.

Hence using the Markov Regime-switching model, the current research has tested the following research questions in the Indian Equity market:

- **Procedure adopted for Time-Varying Measure**

1. Identified the total regimes through the likelihood ratio test and different model selection criteria.

2. Applied maximum likelihood estimation method and estimated different equations for different regimes.

3.2.1 Herd Behavior in Size-based Portfolio

This section highlights the testing methodology for identifying herding in different size-based portfolios. First of all, it is necessary to bifurcate the sample companies into size-based portfolios. The following steps are undertaken for bifurcation:

1. Following the methodology of Fama and French (1995), all sample companies have been divided into single sorted portfolios every year during the whole study period.

2. First of all, companies have been arranged in ascending order each year.

3. Median value has been calculated each year.

4. After that, those companies have been identified as large-capitalization companies whose market cap is above the median value, and those companies are identified as small-capitalization companies whose market cap is below the median value.

5. At the end of September each year, a thorough reorganization of the portfolio has been conducted.

6. Each year cross-sectional average returns have been calculated and herding variables like CSAD and market return are computed.

Hence following the above methodology, we have checked the research question as follows:

RQ 1: Does dynamic herd behavior differ between large-capitalization and small-capitalization stocks in the Indian stock market?

3.2.2 Herd Behavior in Volume-based Portfolio

This section highlights the investigation of herd behavior in the volume-based portfolio. To represent volume, every year at the end of each September, several shares traded were collected for all sample companies. The sample companies are divided into high and low-volume companies every year from 2009 to 2023 following Fama and French (1995). The steps for bifurcation are similar to size-based portfolios. Hence, we have addressed the following research question:

RQ 2 Does Dynamic Herd behavior differ in high- and low-volume-based portfolios in the Indian stock market?

3.2.3 Herd Behavior in value and growth stocks

This section highlights the investigation of herding in value and growth stocks. Value stocks are those whose shares are traded at a lower price than their fundamental value. These stocks have a low profit-to-book (PB) ratio, high dividend yield, and low price-to-earnings ratio. Growth stocks are those stocks traded at a higher price than their fundamental value. These stocks have a higher profit-to-book (PB) ratio, low dividend yield, and high price-to-earnings (PE) ratio. To analyze herding among value and growth stocks, we have taken the profit-to-book ratio as a criterion for the bifurcation of sample companies. Each year, the profit-to-book ratio for March is analyzed, and a portfolio is constructed at the end of September

The following steps are undertaken for portfolio formation:

1. To facilitate this process, the selected companies have been organized in ascending order of their profit-to-book ratios as of the end of September each year.

2. Then, the sample companies have been identified as value, neutral, and growth stocks but analysis were performed on value and growth stocks only. The top 30% PB ratio companies are termed as growth stocks, while the bottom 30% PB Ratio companies have been termed as value stocks, and the remaining stocks have been identified as neutral stocks.

3. The variables have been calculated for herding analysis.

RQ 3: Does Dynamic Herd Behavior exist in value and growth stocks in the Indian Stock Market?

4. Empirical Results and Analysis

This part explains the analysis of both linear and Regime-Switching models. First, we describe the variables' characteristics using some stylized facts on return and dispersion. The consequent section encompasses the findings of the Regime Switching model in different factor portfolios.

2.4.1 Stylized Facts

Table 1 explains the stylized facts of market return and cross-sectional absolute dispersion. The mean of CSAD (1.54 per cent) is higher than the market return (0.07 per cent), enabling higher variations in dispersion series than market returns. The standard deviation of the CSAD (0.36 per cent) is less than the market return (1.14 per cent), highlighting the volatility clustering in the dispersion series. Skewness is negative for market returns, indicating the high negative returns while the skewness is positive for CSAD. Moreover, the kurtosis is very high for both the series representing Fat-tails. Furthermore, the jarque-bera statistics are significant, showing a non-normal distribution. The stationarity test (Augmented Dickey-Fuller test) displays that the variables are stationary at level.

The Auto-correlation function at different lags for the CSAD series is significant. It conveys that the dispersion series is positively auto-correlated to higher levels of lags and shows signs of volatility clustering. The ACF of market returns is almost significant at higher lags, and there is no trend in the series. This means the market returns have a lower level of serial correlation with its previous values than the cross-sectional dispersion. These findings are in tune with various earlier studies that applied the Regime Switching models for fat-tails, volatility clustering, and higher serial correlation (Balcilar et al., 2013; Cont, 2010; Fu & Wu, 2021; Sen & Subramaniam, 2019; Singh & Singh, 2017).

Table 1 Stylized Facts

Statistics	CSAD	RM
Mean	1.54%	0.07%
Std.Dev.	0.36%	1.14%
Skewness	2.39	-1.10
Kurtosis	13.96	13.60
Observations	3531	3531
ADF Test	-7.802 ***	-19.86 ***
Jarque-Bera test	21055.95 ***	17275.15 ***
ACF1	0.785	0.159
ACF5	0.627	0.051
ACF20	0.421	-0.000

Source: The authors own computation using E-views 9.0
Notes: ***Significance at 1% level. Jarque-Bera is used to test normality in the series. ACF is the autocorrelation function up to n lags. The Augmented Dickey-Fuller (ADF) test assesses whether a time series is stationary.

2.4.4 Herding Results in Different Factor Portfolios

This study investigates the presence and dynamics of herding behavior in the Indian equity market using a Markov Regime-Switching Model across three volatility regimes—low, high, and extreme—during the period 2009 to 2023. The analysis focuses on different factor-based portfolios constructed using the Fama and French (1995) methodology, specifically portfolios based on market capitalization, trading volume, and Price-to-Book (P/B) ratios. The results indicate that herding behavior is not uniformly present across all portfolios and regimes, but rather is highly regime-dependent, with most herding concentrated in the extreme volatility regime. not attract the same level of attention or imitation, explaining the absence of herding in this segment. These findings are consistent with Chauhan et al. (2020), who observed herding behavior primarily

in large-cap stocks in the Indian market, and Fu and Wu (2021), who attribute such behavior to the influence of institutional attention and media coverage.

Second, regarding Price-to-Book (P/B) ratio-based portfolios, the study finds evidence of herding in value stocks—those with low P/B ratios—during extreme volatility, whereas growth stocks with high P/B ratios do not exhibit herding behavior. This result implies that in times of extreme market stress, investors tend to move collectively into value stocks, possibly perceiving them as undervalued or offering safety through strong fundamentals. Value investors, in particular, often rely on similar fundamental signals such as book value and earnings, and during volatile periods, these signals become more pronounced. As these investors act in unison, either First, in the case of market capitalization-based portfolios, the study finds significant herding behavior in large-cap stocks during extreme volatility, whereas no herding is observed in small-cap stocks. This suggests that during periods of heightened uncertainty, investors tend to follow the actions of others more in large-cap stocks. A plausible explanation is that large-cap stocks receive more attention from institutional investors, analysts, and the media, making them more visible and perceived as relatively stable during turbulent times. This increased attention can lead to a cascading effect where investors mimic trades made by prominent market participants, resulting in herding behavior. In contrast, small-cap stocks typically suffer from lower liquidity, higher information asymmetry, and limited analyst coverage. As a result, they do due to similar strategies or shared analyst recommendations, others may follow, further amplifying the herding effect. On the other hand, growth stocks are usually characterized by higher valuations and expectations about future earnings, making them more volatile and less attractive in uncertain conditions. Investors may be more cautious or divergent in their decisions with these stocks, leading to an absence of herding. These observations align with the findings of Fu and Wu (2021), who noted that herding tends to be more pronounced in undervalued or less speculative stocks during volatile regimes.

Third, the study identifies strong herding behavior in high trading volume portfolios during extreme volatility, while low-volume portfolios show no such behavior. This finding highlights that investors are more likely to imitate others when trading in stocks with high liquidity and trading activity. High-volume stocks are often perceived as safer and easier to exit during uncertain times, attracting more attention from both retail and institutional investors. According to Lan and Lai (2011), liquidity plays a critical role in attracting investors seeking quick returns, especially during volatile periods. Furthermore, high trading volume may serve as a signal that other investors are acting on important information, prompting uninformed or momentum-driven investors to follow their lead, thus contributing to herding behavior. This contrasts with earlier Indian studies, such as those by Garg and Gulati (2013) and Lao and Singh (2011), which found no relationship between herding and trading volume using linear models. However, the current study's use of a nonlinear regime-switching framework allows for a more nuanced understanding of investor behavior under different market conditions, revealing that herding is indeed significant in high-volume stocks, particularly when market volatility is extreme. This finding also mirrors the conclusions of Fu and Wu (2021), who documented similar patterns in the Chinese equity market.

Overall, the study concludes that herding behavior among Indian investors is strongly regime-dependent and is most evident during extreme volatility conditions. Investors are more likely to follow each other when trading in large-cap stocks, value stocks, and high-volume stocks, likely due to greater visibility, analyst coverage, perceived safety, and liquidity. In contrast, small-cap stocks, growth stocks, and low-volume stocks exhibit no significant herding, suggesting more independent or less coordinated investor behavior in those segments. These insights have important implications for understanding investor psychology during market stress and can help both regulators and portfolio managers in designing policies and strategies to mitigate the adverse effects of irrational crowd behavior.

CONCLUDING OBSERVATIONS AND PRACTICAL OBSERVATIONS

Our study takes a deep dive into the dynamic nature of herd behavior in the Indian financial market for 2009-2023 using the Markov Regime model. Our study has examined investigated herding in different factor portfolios. We have employed Chang et al. (2000) base model for measuring uniformity among Indian investors. The regime model identifies the three regimes as high (Regime 0), low (regime 1), and extreme volatility regime (Regime 2), respectively. The findings of different factor portfolios have showed significant herding during high volatile regime in low pb ratio stocks (value stocks), high volume stocks, and large capitalization stocks during extremely volatile regimes. The outcomes of current research are useful for stakeholders and market controllers. The investors should form an appropriate strategy to readjust their market portfolio at the time of high volatility or not be captivated by the excess returns created by bubbles in extreme market situations. These results illustrate that the Indian market has become efficient with time as the market regulations continuously improve and information transmission become transparent. Hence, investors should make decisions based on the company's fundamentals, but during any uncertainty, they are exposed to high sentiments and follow each other. Investors need to construct larger portfolios at times of high volatility to maintain the same level of diversification (Chiang & Zheng, 2010; Fu & Wu, 2021). The findings of our study carry important implications for both market regulators and portfolio managers. For regulators, the evidence of significant herding behavior during periods of high and extreme volatility—particularly in value stocks

(low price-to-book ratio), high-volume stocks, and large-cap stocks—signals the need for enhanced market oversight. Real-time monitoring tools should be strengthened to track these segments closely during turbulent periods, as herding can amplify market instability and contribute to the formation of price bubbles. Furthermore, regulators could consider implementing regime-sensitive circuit breakers or volatility controls to curb excessive market movements during times identified as high-risk. Strengthening disclosure requirements during such regimes may also help reduce information asymmetries that fuel herd behavior. In addition, investor education initiatives focusing on the dangers of following the crowd in volatile markets could help promote more rational decision-making among retail investors.

Table 2 Estimation Outcomes of Regime Switching Model in Factor-Based Portfolios (2-Class)

Coefficients	Large Cap	Small Cap	High PB	Low PB	High Volume	Low Volume
γ_{00}	0.006***	0.008***	0.006***	0.009***	0.007***	0.006***
γ_{01}	0.005***	0.006***	0.005***	0.007***	0.005***	0.005***
γ_{02}	0.006***	0.009***	0.008***	0.011***	0.006***	0.008***
γ_{10}	0.109***	0.124***	0.143***	0.153***	0.100***	0.129***
γ_{11}	0.089***	0.133***	0.155***	0.142***	0.083***	0.153***
γ_{12}	0.313***	0.184***	0.295***	0.255***	0.287***	0.222***
γ_{20}	1.597***	-0.420	1.154***	-0.917	0.672***	1.164***
γ_{21}	2.762**	1.113***	0.984***	-0.342	1.794***	0.637
γ_{22}	-0.942**	-0.218	-0.910	-0.864*	-0.927***	-0.425*
γ_{3}	0.352***	0.353***	0.334***	0.272***	0.360***	0.379***
γ_{4}	0.116***	0.121***	0.130***	0.115***	0.149***	0.116***
σ_{0}	0.0017***	0.002***	0.002***	0.002***	0.002***	0.018***
σ_{1}	0.0011***	0.001***	0.001***	0.001***	0.001***	0.013***
σ_{2}	0.003***	0.002***	0.004***	0.004***	0.004***	0.003***
P_{00}	0.92	0.97	0.96	0.95	0.93	0.96
P_{11}	0.95	0.98	0.95	0.97	0.97	0.97
P_{22}	0.83	0.98	0.95	0.91	0.70	0.97
N_{0}	1731	1369	1880	1725	1082	1669
N_{1}	1449	1818	1460	1580	2252	1579
N_{2}	349	342	189	224	195	281
N	3529	3529	3529	3529	3529	3529
τ_{0}	17.66	65	34.18	35.20	22.54	43.92
τ_{1}	27.34	113	31.06	42.70	64.34	47.85
τ_{2}	7.27	57	23.63	16	3.55	46.83
AIC	-9.768	-9.5911	-9.656	-9.162	-9.515	-9.857
LOG L	17256.99	16943.648	17058.039	16187.13	16810.62	17414.29
LR TEST	1026.5***	516.20**	788.60***	606.49***	818.25***	595.03***

Source: Authors' own computation using Ox-metrics 7.0

Notes: AIC is the information criterion. LOG L is log-likelihood. PB is the Market-to-Book Ratio. * Denotes significance at the 10% level, indicating moderate statistical evidence. ** Denotes significance at the level of 5%, reflecting a stronger level of statistical evidence. *** Denotes significance at the level of 1%, suggesting a very high level of statistical significance.

For portfolio managers, the dynamic nature of herding across regimes calls for more adaptive investment strategies. Integrating regime-switching models into portfolio construction and risk management processes can help managers adjust asset allocations in response to shifting market conditions. For example, given the observed tendency for herding in value and large-cap stocks during volatile periods, managers might reduce exposure to these segments or employ hedging strategies during such times. The findings also open up opportunities for contrarian investment approaches, where mispricings created by herd-driven behavior can be exploited. Additionally, behavioral indicators derived from herding dynamics can be incorporated into asset selection and timing strategies, enhancing overall portfolio performance. Ultimately, understanding the regime-dependent nature of herding behavior enables both regulators and market participants to respond more effectively to market risks and inefficiencies.

We only consider static transition probabilities in the study. Further research can be conducted by considering the impact of other exogenous variables like market sentiments or other global factors on herding through the time-varying transition probabilities regime model. Moreover, one can differentiate between different types of herding as we measured herding at market consensus.

REFERENCES

i. Ansari, A., & Ansari, V. A. (2021). Do investors herd in emerging economies? Evidence from the Indian equity market. Managerial Finance, 47(7), 951–974. https://doi.org/10.1108/MF-06-2020-0331

ii. Avery, C., & Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets. American Economic Review, 88(4), 724–748. https://doi.org/10.2307/117003

iii. Babalos, V., Balcilar, M., & Gupta, R. (2015). Herding behavior in real estate markets: Novel evidence from a Markov-switching model. Journal of Behavioral and Experimental Finance, 8, 40–43. https://doi.org/10.1016/J.JBEF.2015.10.004

iv. Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. Journal of International Financial Markets, Institutions and Money, 23(1), 295–321. https://doi.org/10.1016/J.INTFIN.2012.09.007

v. Benkraiem, R., Bouattour, M., Galariotis, E., & Miloudi, A. (2021). Do investors in SMEs herd? Evidence from French and UK equity markets. Small Business Economics, 56(4), 1619–1637. https://doi.org/10.1007/S11187-019-00284-0

vi. Bhatia, M. (2022). Stock Market Efficiency and COVID-19 with Multiple Structural Breaks: Evidence from India. Global Business Review. https://doi.org/10.1177/09721509221110372

vii. Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. Journal of Political Economy, 100(5), 992–1026. https://www.jstor.org/stable/2138632

viii. Bohl, M. T., Klein, A. C., & Siklos, P. L. (2016). A Markov Switching Approach to Herding. Credit and Capital Markets – Kredit Und Kapital, 49(2), 193–220. https://doi.org/10.3790/CCM.49.2.193

ix. Brooks, C. (2008). Introductory Econometrics for Finance (2nd ed.). Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9780511841644

x. Brooks, C. (2019). Introductory Econometrics for Finance (4th ed.). Cambridge University Press. https://doi.org/DOI: 10.1017/9781108524872

xi. Campbell, J. Y., Lo, A. W. (Andrew W.-C., & MacKinlay, A. C. (1997). The econometrics of financial markets. Princeton University Press.

xii. Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An inter natioal perspective. Journal of Banking & Finance, 24(10), 1651–1679. https://doiorg/DOI: 10.1080/1540496X.2019.1641082

xiii. Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. Journal of Bank ing and Finance, 34(8), 1911–1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

xiv. Choi, K. H., & Yoon, S. M. (2020). Investor sentiment and herding behavior in the korean stock market. Internation al Journal of Financial Studies, 8(2), 34. https://doi.org/10.3390/ijfs8020034

xv. Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd around the Market? Financial Analysts Journal, 51(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

xvi. Cont, R. (2010). Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, 1(2), 223–236. https://doi.org/10.1080/713665670

xvii. Davies, R. B. (1987). Hypothesis Testing when a Nuisance Parameter is Present Only Under the Alternatives. Bio metrika, 74(1), 33. https://doi.org/10.2307/2336019

xviii. Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. The Journal of Fi nance, 50(1), 131–155. https://doi.org/10.1111/j.1540-6261.1995.tb05169.x

xix. Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. Journal of Finance, 51(1), 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

xx. Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1–22. https://doi.org/10.1016/J.JFINECO.2014.10.010

xxi. Fu, J., & Wu, L. (2021). Regime-switching herd behavior: Novel evidence from the Chinese A-share market. Fi nance Research Letters, 39, 101652. https://doi.org/10.1016/J.FRL.2020.101652

xxii. Ganesh, R., Naresh, G., & Thiyagarajan, S. (2017). The reflection of crowd behaviour in Indian bourses. Internation al Journal of Behavioural Accounting and Finance, 6(2), 93. https://doi.org/10.1504/IJBAF.2017.086408

xxiii. Garg, A., & Gulati, R. (2013). Do investors herd in Indian market. DECISION, 40(3), 181–196. https://doi. org/10.1007/S40622-013-0015-Z

xxiv. Gleason, K. C., Mathur, I., & Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector ETFs. Journal of Empirical Finance, 11(5), 681–694. https://doi.org/10.1016/j.jempfin.2003.06.003

xxv. Guo, F., Chen, C. R., & Huang, Y. S. (2011). Markets contagion during financial crisis: A regime-switching ap proach. International Review of Economics & Finance, 20(1), 95–109. https://doi.org/10.1016/J.IREF.2010.07.009

xxvi. Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, 57(2), 357. https://doi.org/10.2307/1912559

xxvii. Hung, N. T. (2019). Return and volatility spillover across equity markets between China and Southeast Asian coun tries. Journal of Economics, Finance and Administrative Science, 24(47), 66–81. https://doi.org/10.1108/JE FAS-10-2018-0106/FULL/PDF

xxviii. Hwang, S., & Salmon, M. (2004). Market stress and herding. Journal of Empirical Finance, 11(4), 585–616. https:// doi.org/10.1016/J.JEMPFIN.2004.04.003

xxix. Javaira, Z., Sahar, N. U., Hashmi, S. D., & Naz, I. (2024). Volatility and Dynamic Herding in Energy Sector of Devel oped Markets During COVID-19: A Markov Regime-Switching Approach. Fudan Journal of the Humanities and So cial Sciences, 17(1), 115–138. https://doi.org/10.1007/S40647-023-00395-9/METRICS

xxx. Jebran, K., & Iqbal, A. (2016). Examining volatility spillover between Asian countries' stock markets. China Finance and Economic Review, 4(1), 1–13. https://doi.org/10.1186/S40589-016-0031-1/TABLES/5

xxxi. Kabir, M. H., & Shakur, S. (2018). Regime-dependent herding behavior in Asian and Latin American stock markets. Pacific-Basin Finance Journal, 47, 60–78. https://doi.org/10.1016/J.PACFIN.2017.12.002

xxxii. Kanojia, S., Singh, D., & Goswami, A. (2022). Impact of herding on the returns in the Indian stock market: an empiri cal study. Review of Behavioral Finance, 14(1), 115–129. https://doi.org/10.1108/RBF-01-2020-0017/FULL/XML

xxxiii. Kapoor, S., & Prosad, J. M. (2017). Behavioural Finance: A Review. Procedia Computer Science, 122, 50–54. https://doi.org/10.1016/J.PROCS.2017.11.340

xxxiv. Klein, A. C. (2013). Time-variations in herding behavior: Evidence from a Markov switching SUR model. Journal of International Financial Markets, Institutions and Money, 26, 291–304. https://doi.org/10.1016/j.intfin.2013.06.006

xxxv. Kumar, A., Bharti, & Bansal, S. (2016). An Examination of Herding Behavior in an Emerging Economy-A Study of Indian Stock Market. Global Journal of Management and Business Research, 16.

xxxvi. Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. Journal of Financial Economics, 32(1), 23–43. https://doi.org/10.1016/0304-405X(92)90023-Q

xxxvii. Lao, P., & Singh, H. (2011). Herding behaviour in the Chinese and Indian stock markets. Journal of Asian Econom ics, 22(6), 495–506. https://doi.org/10.1016/j.asieco.2011.08.001

xxxviii. Mand, A. A., & Sifat, I. (2021). Static and regime-dependent herding behavior: An emerging market case study. Jour nal of Behavioral and Experimental Finance, 29, 100466. https://doi.org/10.1016/J.JBEF.2021.100466

xxxix. Mertler, C. A., Vannatta, R. A., & LaVenia, K. N. (2021). Advanced and Multivariate Statistical Methods : Practical Application and Interpretation (7th ed.). Routledge. https://doi.org/10.4324/9781003047223

xl. Mukherjee, P., & Tiwari, S. (2022). Trading Behaviour of Foreign Institutional Investors: Evidence from Indian Stock Markets. Asia-Pacific Financial Markets, 29(4), 605–629. https://doi.org/10.1007/s10690-022-09361-z

xli. Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Con sistent Covariance Matrix. Econometrica, 55(3), 703–708. https://doi.org/10.2307/1913610

xlii. Noor, N. M., Al Bakri Abdullah, M. M., Yahaya, A. S., & Ramli, N. A. (2015). Comparison of Linear Interpolation Method and Mean Method to Replace the Missing Values in Environmental Data Set. Materials Science Forum, 803, 278–281. https://doi.org/10.4028/WWW.SCIENTIFIC.NET/MSF.803.278

xliii. Poshakwale, S., & Mandal, A. (2014). Investor Behaviour and Herding: Evidence from the National Stock Exchange in India: Journal of Emerging Market Finance, 13(2), 197–216. https://doi.org/10.1177/0972652714541341

xliv. Rubbaniy, G., Ali, S., Abdennadher, S., & Siriopoulos, C. (2025). Financial Market Determinants of Dynamic Herd ing in North American Energy Equity Market. International Journal of Finance & Economics. https://doi.org/10.1002/IJFE.3165

xlv. Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. The American Economic Review, 80(3), 465–479. https://doi.org/10.2307/2006678

xlvi. Sen, R., & Subramaniam, M. (2019). Stylized Facts of the Indian Stock Market. Asia-Pacific Financial Markets, 26(4), 479–493. https://doi.org/10.1007/S10690-019-09275-3

xlvii. Sharma, A., & Kumar, A. (2020). A review paper on behavioral finance: study of emerging trends. Qualitative Re search in Financial Markets, 12(2), 137–157. https://doi.org/10.1108/QRFM-06-2017-0050/FULL/XML

xlviii. Singh, A., & Singh, M. (2017). Risk–Return Relationship in BRIC Equity Markets: Evidence from Markov Regime Switching Model with Time-varying Transition Probabilities: Metamorphosis: A Journal of Management Research, 15(2), 69–78. https://doi.org/10.1177/0972622516675814

xlix. Stavroyiannis, S., & Babalos, V. (2020). Time-varying herding behavior within the Eurozone stock markets during crisis periods: Novel evidence from a TVP model. Review of Behavioral Finance, 12(2), 83–96. https://doi.org/10.1108/ RBF-07-2018-0069/FULL/XML

l. Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. Pacific Basin Finance Journal, 16(1–2), 61–77. https://doi.org/10.1016/j.pacfin.2007.04.004

li. www.moneycontol.com. (2021). BSE 500 Stock Price, BSE 500 Market Indices, BSE 500 Price, Stock Performance & Comparison. https://www.moneycontrol.com/indian-indices/s&p-bse-500-12.html

lii. Yamaka, W., Phadkantha, R., & Maneejuk, P. (2021). Herding Behavior Existence in MSCI Far East Ex Japan Index: A Markov Switching Approach. Studies in Computational Intelligence, 898, 327–339. https://doi.org/10.1007/978-3-030-48853-6_23/COVER

liii. Yang, W. R., & Chuang, M. C. (2023). Do investors herd in a volatile market? Evidence of dynamic herding in Taiwan, China, and US stock markets. Finance Research Letters, 52, 103364. https://doi.org/10.1016/J.FRL.2022.103364

liv. Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. International Review of Economics & Finance, 29, 12–29. https://doi.org/10.1016/J.IREF.2013.03.002

Organizational Commitment Among Gen Z: The Role of Job Security, Development, and Well-being

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ABSTRACT

This study investigates the influence of job security, training and development opportunities, compensation practices, and employee mental well-being on organizational commitment among Generation Z professionals in the Delhi NCR region. Adopting a mixed-methods approach, both qualitative and quantitative data were gathered to explore the multidimensional nature of organizational commitment. The research employed exploratory and confirmatory factor analysis to validate the factor structure, followed by structural equation modelling to examine relationships among constructs.

The results indicate that job security and training and development have a significant positive impact on employee mental well-being, which, in turn, positively influences organizational commitment. Compensation, while initially considered, did not emerge as a significant direct predictor in the final structural model. Mediation analysis revealed that employee mental well-being fully mediates the relationship between training and development and organizational commitment and partially mediates the relationship between job security and commitment.

These findings align with the Job Demands-Resources (JD-R) model and highlight the growing importance of psychological resources in driving commitment, especially for Gen Z employees who prioritize mental health, personal development, and value-based engagement over traditional job tenures. The study provides actionable insights for organizations to design evidence-based HR strategies that support psychological well-being and foster long-term organizational loyalty in the emerging workforce.

KEYWORDS

Organizational Commitment, Generation Z, Job Security, Training and Development, Mental Well-being, Compensation.

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INTRODUCTION

Organizational commitment is widely recognized as a pivotal construct influencing employee behaviour and, consequently, organizational performance. It transcends the traditional boundaries of job satisfaction or momentary engagement by encapsulating employees' emotional attachment, identification with organizational values, and willingness to exert discretionary effort for the achievement of organizational goals. Employees demonstrating high levels of organizational commitment are more likely to remain with the organization, contribute proactively, and exhibit a heightened sense of responsibility toward their roles.

The essence of organizational commitment lies in the creation of a supportive and inclusive work environment where employees feel valued, empowered, and aligned with the mission and vision of the organization. Unlike superficial incentives or temporary perks, organizational commitment is fostered through deeper cultural dimensions—such as mutual respect, open communication, and trust in leadership. When employees perceive that their contributions are acknowledged and their well-being prioritized, they are more inclined to internalize organizational goals and sustain long-term engagement.

Organizational commitment is shaped by a confluence of factors, including job security, training and development opportunities, mental well-being, and compensation practices. Job security serves as a psychological anchor, allowing employees to focus on their tasks without anxiety over employment continuity. Equally, access to continuous professional development and upskilling initiatives reflects an organization's commitment to employee growth, fostering a sense of loyalty and preparedness for future roles. Mental well-being has emerged as a critical dimension of commitment, wherein psychological safety, stress management, and emotional support significantly impact an employee's capacity and willingness to remain committed. Furthermore, equitable and competitive compensation structures act as tangible validations of employee contributions, reinforcing both satisfaction and organizational loyalty.

Organizational commitment (OC) represents the psychological bond employees develop with their organizations, significantly influencing productivity, retention, and discretionary behavior. While traditional research emphasizes job satisfaction or tenure-based loyalty, modern workforce dynamics—especially among Generation Z—require rethinking commitment paradigms. Gen Z, born between 1997 and 2012, prioritizes meaning, psychological well-being, and growth over stability. Post-pandemic transformations have only heightened the need to investigate their workplace expectations and behaviors

.

This cohort is defined by digital fluency, a strong desire for meaningful work, and elevated expectations regarding corporate social responsibility, diversity, and transparency. Unlike previous generations, Generation Z employees often prioritize growth opportunities, work-life integration, and value alignment over long-term tenure. Their commitment to an organization is thus contingent upon the quality of their experience, including career mobility, flexible work arrangements, and real-time feedback mechanisms. As such, organizational strategies aimed at fostering commitment must evolve to accommodate the unique aspirations of this demographic.

A comprehensive understanding of organizational commitment must integrate these generational insights with evidence-based human resource practices. By aligning organizational goals with the personal and professional aspirations of employees—particularly the emerging Gen Z workforce—organizations can cultivate a committed, resilient, and high-performing workforce. Consequently, organizational commitment becomes a strategic imperative that not only enhances employee retention and productivity but also contributes to sustainable competitive advantage.

Despite a vast body of OC literature, few empirical studies explore OC through the lens of Gen Z in the Indian context, particularly using rigorous statistical tools such as SEM. Most Indian studies emphasize older generational cohorts or IT/ITES sectors, neglecting the growing Gen Z workforce in other service sectors. Thus, this research explores how job security, training and development, compensation, and mental well-being influence Gen Z's organizational commitment in Delhi NCR.

LITERATURE REVIEW

Organizational commitment has been extensively studied over the years, particularly in relation to its influence on employee retention, performance, and engagement. However, there remains a gap in understanding how this concept applies specifically to Generation Z employees—those born between 1997 and 2012—who exhibit unique preferences, work values, and expectations. While prior studies have established a range of independent variables (IDVs) that influence organizational commitment, including job security, training and development, compensation practices, and employee well-being, there is a need to re-examine these within the context of Gen Z. To identify relevant constructs, a comprehensive literature review was conducted that drew upon multiple theoretical models, such as Meyer and Allen's Three-Component Model of Commitment, the Social Exchange Theory, and the Job Demands-Resources Model. These models provide robust frameworks to explain the psychological mechanisms behind employee attachment to organizations. Accordingly, this study adopts constructs that are strongly supported in literature, ensuring conceptual relevance rather than predefining variables arbitrarily.

Organizational commitment, conceptualized as the psycho-

logical attachment and loyalty of employees to their organizations, is widely regarded as a critical determinant of organizational effectiveness and long-term sustainability. It transcends mere job satisfaction, encompassing affective involvement, normative alignment, and continuance intention (Meyer & Allen, 1997). In the IT sector, where turnover rates are relatively high, understanding the drivers of commitment—particularly among Generation Z employees—is critical for organizational sustainability (Kundu & Gahlawat, 2016). Contemporary organizations operate in increasingly volatile environments, necessitating a reevaluation of the antecedents of commitment—particularly as Generation Z enters the workforce with distinct professional orientations, values, and expectations. This literature review explores four principal antecedents—job security, training and development, compensation practices, and mental well-being—in shaping organizational commitment, particularly through the lens of Generation Z.

Job Security

Historically, job security has been identified as a cornerstone of employee stability and commitment. Employees who perceive their roles as secure are more likely to demonstrate loyalty, reduced turnover intentions, and increased organizational citizenship behaviors (Harvey et al., 2014). However, the notion of job security has undergone a paradigmatic shift in the context of Generation Z. Anand et a. (2023) explores how job security, insecurity, and burnout—framed as COVID-19-related events—affect organizational commitment, using event system theory. Findings show that job insecurity and burnout reduce commitment, even with benevolent leadership as a mediator. Unlike their predecessors, Gen Z employees are less inclined toward lifelong employment in a single organization; rather, they emphasize career resilience, continuous learning, and adaptability (Cleary, 2020). Fleming (2024) argues that for this cohort, perceived employability—the belief in one's capability to obtain and maintain employment—has replaced traditional job security as a driver of organizational attachment. Therefore, fostering psychological security through transparent communication, internal mobility pathways, and skill-based employment strategies is essential to enhancing commitment among Gen Z employees.

Training and Development

Training and development initiatives have long been recognized for their role in building human capital and enhancing organizational commitment. Empirical evidence suggests that when employees perceive developmental opportunities as aligned with their personal and professional aspirations, they are more likely to reciprocate through sustained engagement and commitment (Grossmeier et al., 2020). For Generation Z, such opportunities are not optional but expected. This generation values organizations that prioritize upskilling, mentorship, and digital learning (Cvenkel, 2020). Furthermore, Haddon (2018) notes that interactive, gamified, and mobile-friendly learning modalities resonate more effectively with Gen Z's learning preferences. By integrating training as a strategic and individualized initiative, organizations can reinforce employees' perceptions of being valued and invested in, thereby fostering long-term organizational allegiance. Pandita and Kumar (2022) investigates job engagement (JOB) drivers among Gen Z in India's IT sector, focusing on perceived organizational support (POS), supervisor support (PSS), and co-worker relationships (COP). Based on 302 survey responses and structural equation modeling, all three factors positively influence JOB, with PSS having the strongest impact. Findings offer actionable insights for HR strategies to engage and retain Gen Z in IT companies.

Compensation Practices

Compensation is traditionally viewed as a fundamental hygiene factor in Herzberg's two-factor theory, essential for preventing dissatisfaction but not necessarily enhancing motivation. However, for Generation Z, compensation is evaluated through a more holistic and equitable lens. GIGI and Pavithra (2020) emphasize that while financial remuneration remains important, Gen Z also values non-monetary benefits such as wellness stipends, educational subsidies, and corporate social responsibility engagement. Graveling et al. (2008) support this assertion by noting that equitable compensation—perceived not just in monetary terms but in fairness and transparency—positively correlates with affective commitment. Haddon (2018) further highlights that compensation structures aligned with personal well-being and life goals significantly influence Gen Z's organizational attachment. Thus, designing inclusive and equitable compensation packages is imperative for cultivating sustained organizational commitment in the emerging workforce.

Mental Well-Being

Mental well-being, often overlooked in traditional organizational commitment models, has recently emerged as a pivotal determinant of employee loyalty and performance. In the wake of increasing workplace stressors, including technological overload and economic uncertainty, Generation Z exhibits heightened sensitivity to psychological safety, emotional health, and work-life integration (Grossmeier et al., 2020). Harvey et al. (2014) found that organizations failing to address mental health concerns experienced increased absenteeism, reduced engagement, and diminished organizational commitment. Cleary (2020) posits that Gen Z employees actively seek organizations that normalize mental health discourse and embed psychological safety into workplace culture.

Effective mental well-being strategies include offering mental health days, access to professional counselling, flexible work arrangements, and stress management workshops.

Haddon (2018) further notes that fostering open communication and empathetic leadership practices enhances psychological safety and strengthens employees' emotional bonds with the organization. Furthermore, mental well-being is interdependent with other factors—job insecurity exacerbates stress, inadequate training increases performance anxiety, and compensation that neglects wellness needs undermines trust (Fleming, 2024). Organizations that proactively integrate mental health into their human resource strategies are more likely to foster resilient and committed teams. According to Jain and Singhal (2020), organizations that implement wellness programs and foster inclusive cultures see a positive impact on organizational commitment.

While organizational commitment has been extensively studied over the decades, most existing research primarily focuses on older generational cohorts such as Baby Boomers, Gen X, and Millennials (Meyer & Allen, 1997). These studies often assume homogeneity in employee expectations and motivational drivers, overlooking the unique psychological, social, and occupational characteristics of Generation Z (Cleary, 2020; Cvenkel, 2020), who are now entering the workforce in significant numbers.

Moreover, traditional models of organizational commitment have largely emphasized structural factors such as compensation and job tenure, with relatively limited integration of mental well-being as a mediating construct, especially for the Gen Z demographic (Grossmeier et al., 2020; Harvey et al., 2014). As Gen Z exhibits heightened awareness of mental health and prioritizes meaningful work and psychological safety, a fresh evaluation of commitment antecedents is necessary (Fleming, 2024; Haddon, 2018).

Although some emerging literature addresses Gen Z's workplace behavior, empirical studies linking job security, training and development, compensation, and employee mental well-being with organizational commitment in an integrated framework remain scarce—particularly within the Indian context and urban corporate environments like Delhi NCR (Jehanzeb & Bashir, 2013; GIGI & Pavithra, 2020). Additionally, there is minimal use of robust analytical tools such as Structural Equation Modelling (SEM) in this specific thematic area, limiting our understanding of complex interrelationships and mediating effects (Bakker & Demerouti, 2007).

The integration of these four antecedents within commitment frameworks reflects a shift from transactional to transformational paradigms of employee engagement. Where earlier models emphasized economic exchanges, contemporary approaches underscore psychological contracts and emotional resonance. Generation Z, shaped by global uncertainty, rapid technological advancement, and heightened social awareness, seeks alignment between personal values and organizational practices. As such, antecedents of organizational commitment must be reconceptualized to include both traditional structural supports and emergent psychological needs.

Theoretical Model

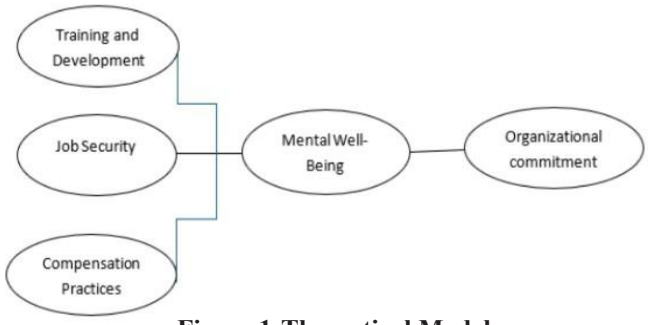

Figure 1:Theoretical Model

Objective and Hypothesis

To examine the influence of job security, training and development, compensation, and mental well-being on organizational commitment among Gen Z, and to assess the mediating role of mental well-being.

Hypotheses

H_1: Job security has a significant positive impact on Organizational Commitment for Gen Z.

H_2: Training and development opportunities positively influence Organizational Commitment for Gen Z.

H_3: Employees' mental well-being a significant positive impact on Organizational Commitment for Gen Z.

H_4: Compensation practices have a significant positive impact on Organizational Commitment for Gen Z.

H_{5a}: Employee Mental Well-being mediates the relationship between Job Security and Organizational Commitment.

H_{5b}: Employee Mental Well-being mediates the relationship between Training and Development and Organizational Commitment.

H_{5c}: Employee Mental Well-being mediates the relationship between Compensation Benefits and Organizational Commitment.

RESEARCH METHODOLOGY AND DATA ANALYSIS

This study adopts a mixed-methods research approach, integrating both qualitative and quantitative methods to comprehensively explore the interconnectedness of job security, training & development opportunities, mental wellbeing and compensation in fostering Organizational Commitment.

The combination of these methodologies ensures a holistic understanding of the research problem, allowing for both statistical validation and in-depth analysis.

The research variables considered in this study include compensation, job security, and training and development as independent variables, while Organizational Commitment serves as the dependent variable. The study targets working professionals in the Delhi NCR region, covering various industries and organizational structures. Employees working in different organizations across Delhi NCR form the unit of study.

A convenience sampling technique was employed to collect data from respondents. This non-probability sampling method was chosen based on the characteristics of the population and the objectives of the study. Respondents were screened based on their birth years (1997–2012) to ensure they belonged to Generation Z in the banking, retail, and education sectors. A preliminary question in the questionnaire ensured age-appropriate inclusion. Only responses from those falling into the Gen Z age bracket at the time of the study were considered for final analysis. The final sample size consists of 146 (Belonging to Gen Z) working professionals in Delhi NCR comprising of seventy-one females and seventy-five males were analysed. Data for this study was collected from both primary and secondary sources. Primary data was gathered through a structured questionnaire designed by the researcher, which aimed to collect responses on employee well-being, mental health, and key variables such as compensation, training and development, job security. Secondary data was sourced from journal articles, internet resources, blogs, and magazines relevant to the study's scope.

A questionnaire consisting of 25 questions, including demographic variables, was used to gather primary data. Study questions gathered responses on 5-point Likert Scale. The questionnaire was designed to measure key aspects of Organizational Commitment, job security, compensation, training, and stress levels in the workplace. To assess the feasibility of the study, a pilot study was conducted with 30 randomly selected respondents. After analysing the collected data, necessary corrections and modifications were made to the questionnaire to ensure clarity and reliability.

Exploratory and confirmatory factor analysis

For data analysis, Exploratory Factor Analysis (EFA) was conducted initially to identify the underlying factor structure of the items and to examine the dimensionality of each construct.

Principal Component Analysis with Varimax rotation was used, and factor loadings above 0.5 were considered significant. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were used to assess the suitability of the data for factor analysis.

The measure of sampling adequacy i.e., Kaiser- Meyer-Olkin (KMO) measure which evaluates the proportion of variance in observed variables that might be caused by underlying factors is 0.745 which is above .65 (threshold limit) for various factors related to Organizational commitment for Gen Z. Thus, select items are appropriate to conduct an exploratory factor analysis. Bartlett's Test of Sphericity tests the significance of overall correlation among the items used for EFA, which was found to be significant with chi-square = 1409.234, p=0.000, for the constructs. EFA can be performed on the given set of data. The EFA derives seven constructs were identified whose eigenvalue is greater than 1. These seven constructs explain a total of 69.53 %. of variance, The Varimax rotation refines the factor structure. Seven factors were identified through EFA and labelled based on the characteristics of the items clubbed under each factor based on factor loadings. These identified constructs are labelled as Training and Development (TD), Job Security (JS), Compensation Benefits (CB), Organizational Commitment (OC), Employee Mental Well Being (EMWB), Employee Engagement (EE), and Employee Well-being Initiatives (EWBI). Also, factor loadings of items and Cronbach's Alpha values of identified factors are given in Table 1. The Cronbach's Alpha value Employee Engagement (EE), and Employee Well-being Initiatives (EWBI) are 0.644 and 0.587 respectively which is moderately acceptable as threshold limit is 0.60. Given this, its inclusion in Confirmatory Factor Analysis (CFA) requires careful evaluation. Following EFA, Confirmatory factor analysis is employed to confirm reliability and validity of the structure. It assesses construct reliability (CR), average variance extracted (AVE), and factor loadings to determine whether Employee Engagement (EE), and Employee Well-being Initiatives (EWBI) meets the necessary reliability and validity criteria. If necessary, revising or removing weak items may improve internal consistency.

Final first order confirmatory factor model was subject for evaluation of reliability and validity. As discussed above to improve internal consistency, validity and model fit indices both Employee Engagement (EE), and Employee Well-being Initiatives (EWBI) has been dropped from the final first order CFA output. The Construct reliability and average variance extracted for each factor given in table 1. A combination of absolute, incremental and parsimony fit indices are used to evaluate the goodness of fit of the final first order CFA model(given in table 3) such as chi-square (χ^2) statistics, chi-square/ df (CMIN/DF), the root mean squared error of approximation (RMSEA),

Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Normed Fit Index (NFI). The goodness of fit indices for the final first order confirmatory model given is as follows: Chi-square (χ^2) statistics is 175.382 with 109 degree of freedom and p=0.00, chi-square/ df (CMIN/DF) is 1.609, RMSEA is 0.065, CFI is 0.94, TLI is 0.925, and NFI is 0.858.

Table 1: Factor Loading of Rotated Component Matrix, Cronbach alpha, Standardized Regression Weights of CFA with Construct Reliability and Discriminant Validity

Factors	Items	Source for Adaptation	Factor Loadings	Cronbach's Alph	Standardized Regression Weights	CR	AVE	MSV	ASV
Training and Development (TD)	Q25 Training and development helped me in the both personal and professional development.	Jehanzeb, Bashir, (2013); Ahmad, & Bakar (2003)	.927	0.827	.979	0.851	0.608	0.092	0.050
	Q24 My organization has training and development policy applicable to all the employees		.925		.950				
	Q23 My training sessions helps in increasing my productivity at work		.686		.516				
	Q22 I am satisfied with the training being imparted by my organization		.553		.552				
Job Security (JS)	Q19 I am satisfied with the level of job security provided by the organisation	Ashford et al. (1989). De Witte, (2005)	.810	0.793	.826	0.802	0.507	0.329	0.187
	Q20 I am satisfied with the level of job security my current position offers		.779		.619				
	Q18 I feel comfortable about the stability of my job in organization		.645		.703				
	Q21 I feel valued and secured in my role within the workplace		.640		.683				
Compensation Benefits (CB)	Q3 I am satisfied with the bonus scheme in my company	GIGI & Pavithra. (2020); Graveling, et al. (2008)	.866	0.816	.900	0.824	0.614	0.092	0.030
	Q2 I am satisfied with the retirement benefit plans from my organization		.835		.787				
	Q6 My organization provides insurance scheme for me and my family		.820		.642				
Organizational Commitment (OC	Q12 I enjoy discussing my organization with people outside it	Meyer & Allen, (1997); Ryan & Deci. (2000).	.817	0.780	.739	0.780	0.542	0.329	0.158
	Q13 I really feel as if this organization's problems are my own		.779		.738				
	Q14 I feel like part of the family at my organization		.720		.731				
Employee Mental Well Being (EMWB)	Q16 I often feel emotionally drained after work	Grossmeier et al. (2020); Harvey et al. (2014)	.857	0.761	.836	0.776	0.539	0.280	0.153
	Q17 I feel that my organization values employee's wellbeing and takes proactive steps to manage workplace stress		.785		.724				
	Q15 I feel comfortable discussing my stress or mental health concerns with my senior		.639		.628				

Factors	Items	Source for Adaptation	Factor Loadings	Cronbach's Alph	Standardized Regression Weights	CR	AVE	MSV	ASV
Employee Engagement (EE)	Q7 Organization conducts engagement activities timely to keep me engaged	Haddon (2018); Cvenkel (2020)	.835	0.644	Dropped in CFA due to Reliability and Convergent validity issues				
	Q8 I want my organization to conduct engagement activities more frequently		.759						
	Q9 Engagement activities help me relieve my stress		.625						
Employee Well-being Initiatives (EWBI)	Q5 Team outings are organized by the organization	Grossmeier et al. (2020); Fleming (2024)	.803	0.587	Dropped in CFA due to Reliability and Convergent validity issues				
	Q4 My organization provide frequent medical checkups for the employees		.781						

Table 1 shows that the average variance extracted (AVE) of all five latent constructs of is greater than the threshold value of 0.5 (Hair et al. 2015). Construct reliability (CR) for all six constructs is greater than the threshold value of 0.7 (Hair et al. 2015). Discriminant Validity is established if variance estimates are greater than the squared correlation estimate (Fornell & Larcker, 1981).

Relationships and Testing of Hypothesis

Final first order CFA model was further scrutinized for testing the relationship between various constructs. Figure 2 demonstrates the initial SEM model involving all paths between independent and dependent variables. Figure 3 presents the final mediation model, a few constructs that have the Insignificant paths were removed based on significance of standardized regression weights and their significance value. Standardized regression coefficients and their t- values obtained in the structural equation model (fig 3) are given in table 1. There is a direct positive impact of Job Security (JS) and training and development (TD) on Employee Mental Well Being (EMWB) with unstandardized regression coefficient B=0.473, 0.197, t=4.747, 2.310, p=***, 0.021<0.01 respectively with standardized regression coefficient as β=0.479 and 0.201 respectively. It also suggests there is a direct positive impact of Job security (JS) and Employee Mental Well Being (EMWB) on Organizational Commitment (OC), with unstandardized regression coefficient B=0.429, 0.259, t=2.212, 2.212, p=***, 0.027<0.01 respectively with standardized regression coefficient as β=0.437and 0.260 respectively.

Mediation: The mediation analysis in this study was conducted using the widely accepted procedure proposed by Baron and Kenny (1986) to examine whether employee mental well-being mediates the relationships between key organizational factors (job security, training and development, and compensation benefits) and organizational commitment among Generation Z employees. Following the four-step regression approach, we tested for (i) a significant total effect of the independent variable on the dependent variable, (ii) a significant effect of the independent variable on the mediator, (iii) a significant effect of the mediator on the dependent variable while controlling for the independent variable, and (iv) a reduction in the direct effect after introducing the mediator.

Complete Mediation: Training and development (TD) significantly impact Employee Mental Well Being (EMWB) and Employee Mental Well Being (EMWB) significantly impact Organizational commitment (OC) whereas Training and development (TD) does not significantly impact Organizational commitment (OC) and had to be removed from the model.

Partial Mediation: Relationships between Job Security (JS) & Employee Mental Well Being (EMWB) is significant; Employee Mental Well Being (EMWB) & Organizational Commitment (OC) is significant; Job Security (JS) and Organizational Commitment (OC) is significant. Standardized regression coefficient is $\beta_{JS\ \&\ EMWB}$= 0.479 and $\beta_{JS\ \&\ OC}$= 0.437 and $\beta_{EMWB\ \&\ OC}$= 0.260. Thus, Employee Mental Well Being (EMWB) is a significant partial mediator in Job Security (JS) and Organizational Commitment (OC).

The findings revealed partial mediation in the relationship between job security and organizational commitment (H_5a), where the inclusion of mental well-being reduced but did not eliminate the direct effect. In contrast, full mediation was found in the case of training and development (H_5b), where the direct effect became non-significant upon including the mediator. No evidence of mediation was observed between compensation benefits and organizational commitment (H_5c), as the conditions outlined by Baron and Kenny were not satisfied. These results underscore the pivotal role of mental well-being in enhancing organizational commitment, particularly in the context of job security and developmental opportunities.

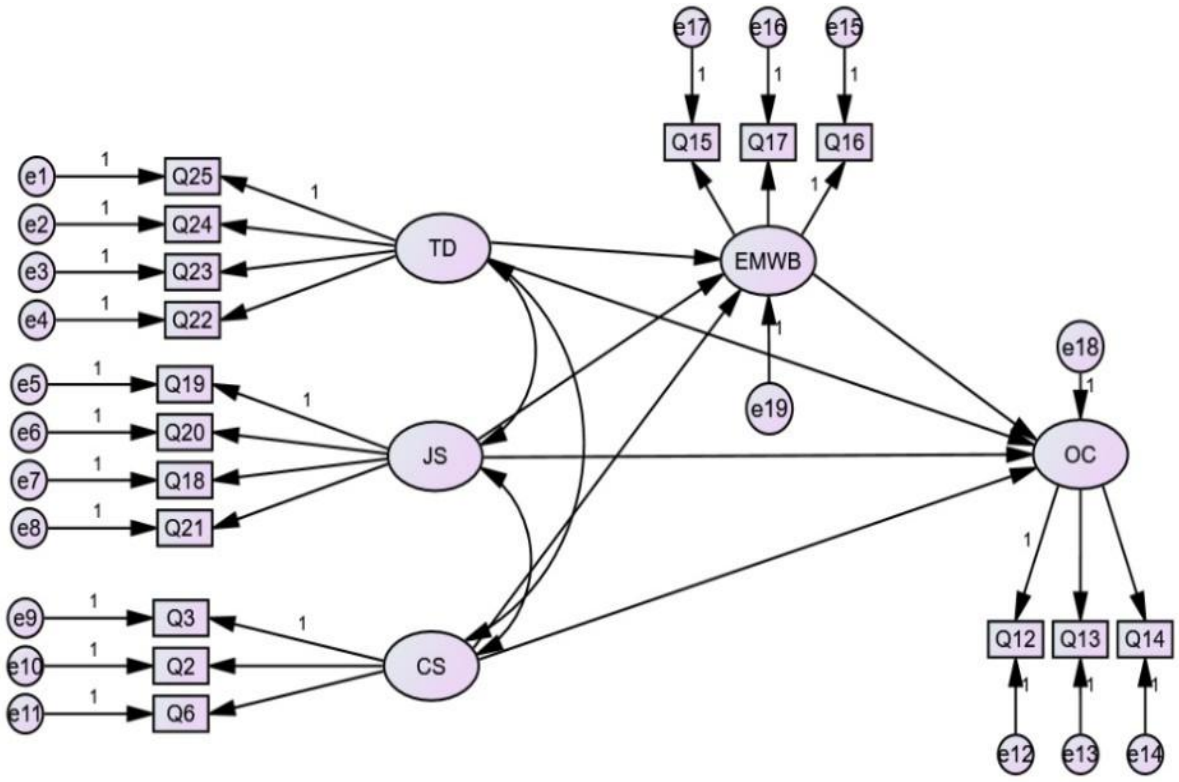

Figure 2: Mediation Model-Input

Following is the table 2 which indicate summary of status of various hypotheses which reflect the relationships being examined in the paper. Table 3 provides the fit indices of the final model with significant paths.

Table2: Summary of Hypotheses Testing Results

S. No	Hypothesis	Status
1	H_1: Job security has a significant positive impact on Organizational Commitment for Gen Z.	Accepted
2	H_2: Training and development opportunities positively influence Organizational Commitment for Gen Z.	Not able to accept
3	Employees' mental well-being a significant positive impact on Organizational Commitment for Gen Z	Accepted
4	H_4: Compensation practices have a significant positive impact on Organizational Commitment for Gen Z.	Not Able to accept
5	H_5a: Employee Mental Well-being mediates the relationship between Job Security and Organizational Commitment.	Partial Mediation
6	H_5b: Employee Mental Well-being mediates the relationship between Training and Development and Organizational Commitment.	Full Mediation
7	H_5c: Employee Mental Well-being mediates the relationship between Compensation Benefits and Organizational Commitment.	Not able to accept

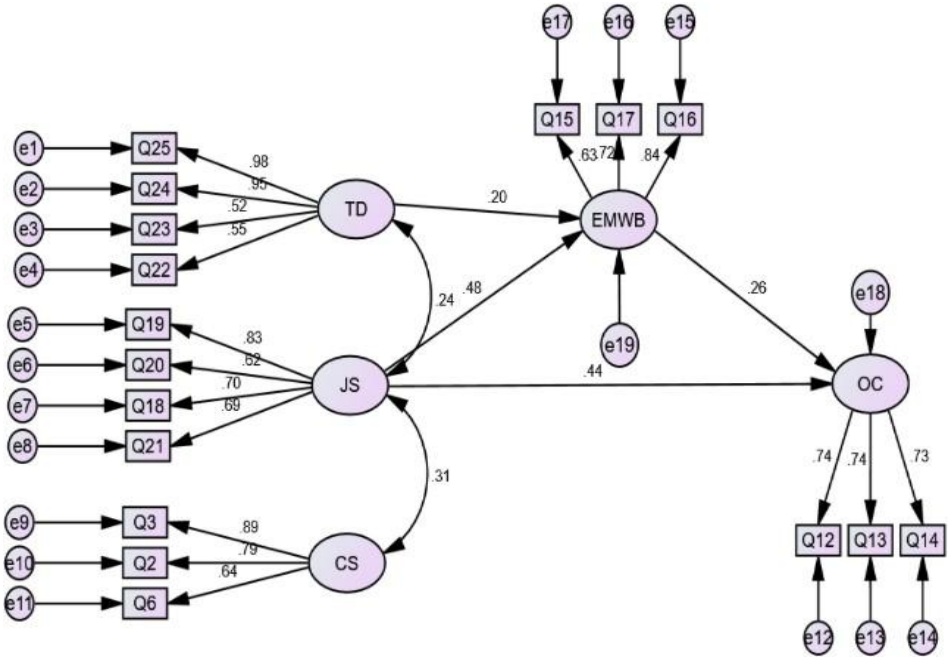

Figure 3: Final Mediation Model-Output

Table 3: Fit indices for Mediation Model

Model Fit Criteria	Parameter	First Order CFA Mode	Mediation Model	Threshold Value N>250 m>30	Decision
Result (Default model)	Chi-Square	175.382	177.107	-	-
	Df	109	113	-	-
	P Value	0.00	0.00	≥ 0.05	-
	CMIN/Df	1.609	1.567	≤ 3.00	Good Fit
Absolute Fit Indices	RMSEA	0.065	0.063	≤ 0.07	Good Fit
Incremental Fit Indices	IFI	0.941	0.943	≥ 0.90	Good Fit
	TLI	0.925	0.930	≥ 0.90	Good Fit
	CFI	0.94	0.942	≥ 0.90	Good Fit
	RFI	0.823	0.828	≥ 0.05	Good Fit
Parsimonious Fit Indices	PNFI	0.688	0.712	≥ 0.5	Good Fit
	PCFI	0.753	0.783	≥ 0.5	Good Fit

CONCLUSION

This study employed a quantitative method research approach to examine how compensation, job security, and training and development influence Organizational Commitment (OC), while exploring the mediating role of Employee Mental Well-being (EMWB) among professionals in the Delhi NCR region. The combination of quantitative and qualitative analyses provided both empirical validation and in-depth insights into the dynamics between the constructs.

The results indicate that Job Security (JS) and Training and Development (TD) have a significant positive effect on EMWB, which in turn positively influences Organizational Commitment. These findings are consistent with prior research. For instance, studies have shown that job security significantly reduces psychological distress and promotes positive workplace attitudes (De Witte, 2005; Cheng & Chan, 2008), thereby enhancing organizational commitment (Ashford et al., 1989). Similarly, training and development opportunities not only improve employee competence but also boost morale and psychological well-being, fostering a greater sense of belonging and commitment to the organization (Jehanzeb & Bashir, 2013; Ahmad & Bakar, 2003).

The study further identified EMWB as a mediator between TD and OC (complete mediation), and between JS and OC (partial mediation). These mediation effects highlight the central role of employee mental well-being in strengthening the link between job resources and organizational outcomes. This aligns with the Job Demands-Resources (JD-R) model, which posits that organizational resources (e.g., training, job security) promote engagement and well-being, which in turn lead to positive outcomes like organizational commitment (Bakker & Demerouti, 2007).

Although compensation benefits (CB) were analyzed, the final structural model emphasizes the more significant influence of developmental and psychological variables, suggesting that intrinsic factors may outweigh extrinsic motivators in fostering long-term commitment—particularly when mediated by employee well-being (Ryan & Deci, 2000).

The validated CFA model demonstrated good fit, and all retained constructs met thresholds for reliability and validity. These findings provide strong empirical evidence supporting the importance of mental well-being in organizational behavior research.

Organizations aiming to enhance employee commitment should focus not only on external rewards such as compensation but also on creating a supportive psychological environment through stable employment and continuous learning opportunities. Promoting mental well-being acts as a catalyst in translating these initiatives into sustained organizational loyalty.

REFERENCES

i. Ahmad, K. Z., & Bakar, R. A. (2003). The association between training and organizational commitment among white-collar workers in Malaysia. International Journal of Training and Development, 7(3), 166–185. https://doi.org/10.1046/j.1360-3736.2003.00182.x

ii. Anand, A., Dalmasso, A., Vessal, S. R., Parameswar, N., Rajasekar, J., & Dhal, M. (2023). The effect of job security, insecurity, and burnout on employee organizational commitment. Journal of Business Research, 162, 113843.

iii. Ashford, S. J., Lee, C., & Bobko, P. (1989). Content, causes, and consequences of job insecurity: A theory-based measure and substantive test. Academy of Management Journal, 32(4), 803–829. https://doi.org/10.5465/256569

iv. Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. Journal of Managerial Psychology, 22(3), 309–328. https://doi.org/10.1108/02683940710733115

v. Cheng, G. H. L., & Chan, D. K. S. (2008). Who suffers more from job insecurity? A meta-analytic review. Applied Psychology, 57(2), 272–303. https://doi.org/10.1111/j.1464-0597.2007.00312.x

vi. Cleary, M. (2020). Mental health and well-being in the workplace: A healthcare perspective. Journal of Workplace Studies, 45(3), 287–299.

vii. Cvenkel, N. (2020). Employee perspectives on mental health and well-being in the workplace: A qualitative analysis. Human Resource Development Review, 19(4), 415–432.

viii. De Witte, H. (2005). Job insecurity: Review of the international literature on definitions, prevalence, antecedents and consequences. SA Journal of Industrial Psychology, 31(4), 1–6. https://doi.org/10.4102/sajip.v31i4.200

ix. Fleming, J. (2024). Employee well-being interventions: A critical analysis. Occupational Health Journal, 52(1), 15–29. GIGI, G. S., & Pavithra, R. (2020). Analyzing mental well-being and organizational outcomes during COVID-19. Journal of Business Studies, 30(2), 112–127.

x. Graveling, R., Crawford, J. O., Cowie, H., Amati, C., & Vohra, N. (2008). Workplace stress and its impact on productivity. International Journal of Workplace Health, 22(1), 45–60.

xi. Grossmeier, J., Hamilton, D., Kirsten, W., Spangler, K., & Smith, S. (2020). Best practices for workplace mental health and well-being interventions. Journal of Employee Well-being, 36(2), 98–112.

xii. Haddon, L. (2018). The role of employee well-being in workplace productivity. HR Management Review, 28(1), 67–82.

xiii. Harvey, S. B., Joyce, S., Tan, L., Johnson, A., Nguyen, H., Modini, M., & Growth, S. (2014). Mental health and work per

formance: A review of the literature. Journal of Occupational Health Psychology, 19(4), 321–345.

xiv. Jain, R., & Singhal, A. (2020). Employee well-being and organizational commitment: A study in Indian IT sector. Journal of Organizational Psychology, 20(1), 52–66.

xv. Jehanzeb, K., & Bashir, N. A. (2013). Training and development program and its benefits to employees and organiza tions: A conceptual study. European Journal of Business and Management, 5(2), 243–252.

xvi. Kundu, S. C., & Gahlawat, N. (2016). Effects of employee retention practices on perceived firm and innovation per formance. International Journal of Innovation and Learning, 19(1), 25-43.

xvii. Meyer, J. P., & Allen, N. J. (1997). Commitment in the workplace: Theory, research, and application. SAGE Publications.

xviii. Pandita, D., & Kumar, A. (2022). Transforming People Practices by Re-Structuring Job Engagement Practices for Generation Z: An Empirical Study. International Journal of Organizational Analysis, 30(1), 115-129.

xix. Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. Con temporary Educational Psychology, 25(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Volatility in the Banking Sector: A Multivariate Study of FPI and Key Economic Indicators

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ABSTRACT

The increasing integration of global financial markets has made emerging economies more vulnerable to cross-border capital movements, especially Foreign Portfolio Investment (FPI). In countries like India, where the banking sector forms a critical pillar of the financial system, the volatility induced by sudden FPI inflows or outflows poses a serious challenge to financial stability. Moreover, macroeconomic conditions such as inflation, interest rates, and exchange rate further compound this volatility. Despite the significance of these variables, limited empirical research has holistically examined how FPI and key economic indicators together influence volatility in the banking sector. This study has investigated the impact of Foreign Portfolio Investment (FPI) and key macroeconomic indicators on volatility in the banking sector. Using a multivariate analytical framework, the research has analyzed the interplay between FPI flows and variables such as interest rates, inflation, and exchange rates. The findings reveal that fluctuations in FPI significantly influenced banking sector volatility, often amplifying market uncertainty during periods of economic or political instability. Additionally, macroeconomic indicators play a critical role in shaping investor behavior and sector performance, with all variables exhibiting stronger correlations with volatility. The study concludes that while FPI has enhanced market liquidity, it has also introduced risks that required careful management through effective regulatory oversight and sound economic policy. The insights provided by this research aimed to assist policymakers and financial institutions in developing strategies to mitigate risk and promote stability within the banking sector.

KEYWORDS

Bank, Exchange, FPI, Inflation, Interest, Nifty, Volatility

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INTRODUCTION

The banking sector plays a pivotal role in the economic development of any nation, acting as the primary conduit between savings and investment. In emerging markets like India, the performance of the banking sector is increasingly influenced by both domestic macroeconomic conditions and international capital flows. Among these, Foreign Portfolio Investment (FPI) has emerged as a significant source of capital that can both stimulate and destabilize financial markets due to its volatile and sentiment-driven nature.

In recent years, increased global financial integration has intensified the sensitivity of banking sector performance to international financial movements. FPIs, being largely speculative in nature, often respond rapidly to changes in global risk sentiment, monetary policies in developed economies, and domestic economic signals. Their entry and exit from emerging markets can lead to substantial fluctuations in equity markets, particularly impacting sectors such as banking which are closely tied to overall economic performance.

In addition to FPI, key economic indicators such as GDP growth, inflation rate, exchange rate fluctuations, interest rate levels, and fiscal policy decisions significantly influence the performance and resilience of banks. These macroeconomic variables affect credit demand, deposit mobilization, non-performing asset (NPA) levels, and profitability metrics within the sector. Hence, a multivariate analytical approach is appropriate to assess the interplay between these factors and to identify the primary drivers of volatility.

Key economic indicators—such as inflation, GDP growth, interest rates, and exchange rates—affect banking operations and investor confidence. High inflation can erode the value of banking assets, while rising interest rates may improve bank margins but also increase the risk of defaults. This complex interplay raises crucial questions: How does FPI interact with macroeconomic fundamentals to influence banking sector volatility? Can we quantify these relationships using a multivariate framework?

Volatility in the banking sector is a critical area of concern for regulators, investors, and policymakers alike. Bank stock indices, such as the Bank Nifty in India, are sensitive not only to domestic economic developments but also to global investment trends and macroeconomic indicators. Inflows and outflows of FPI, often driven by interest rate differentials, geopolitical events, and investor sentiments, can cause sharp fluctuations in the valuation of banking stocks, liquidity positions, and market stability.

Understanding the interplay between FPI flows and macroeconomic indicators is important to comprehend the volatility patterns in the banking sector. A multivariate approach enables a more comprehensive analysis of these interconnected variables. By examining them together, rather than in isolation, the study aims to provide a more candid picture of the causal and correlational dynamics that drive market fluctuations within the banking industry.

Given the recent history of financial turbulence—ranging from the 2008 global financial crisis to the COVID-19 pandemic and subsequent policy shifts—this study is timely and relevant. It seeks to unravel how external capital movements and internal economic indicators jointly influence the banking sector's stability. Such insights are not only academically valuable but also carry significant policy implications in areas such as capital control measures, banking regulation, and monetary policy calibration.

In this context, the study proposes to analyze the volatility in the banking sector using a multivariate time series approach, incorporating FPI data and selected macroeconomic indicators. By identifying significant determinants and modeling their interactions, the research seeks to offer insights for policymakers, investors, and financial analysts navigating an increasingly interconnected global financial environment.

LITERATURE REVIEW

Foreign Portfolio Investment (FPI) is known for its dynamic nature and potential to influence financial market volatility, especially in emerging economies. According to Bekaert and Harvey (2000), liberalization in capital markets often leads to a surge in FPI inflows, which can initially boost market liquidity but may also increase vulnerability to external shocks. Their findings emphasized that capital inflows can lead to both higher returns and higher volatility, especially in sectors like banking, which are sensitive to interest rates and economic sentiment. Anand and Tiwari (2011) used time-series models to show that abrupt FPI outflows can trigger significant stock price corrections in banking and financial stocks, leading to systemic concerns.

Similarly, Rai and Bhanumurthy (2004) examined FPI flows into India and concluded that these investments were highly responsive to both domestic macroeconomic indicators and global financial conditions. They have argued that FPI, driven by short-term considerations, tends to amplify volatility rather than stabilize markets.

Ghosh, Saidi, and Johnson (1999) also noted that portfolio flows tended to be more volatile than foreign direct investment (FDI), as they were easily reversible. They suggested that countries with weaker financial infrastructures were more susceptible to the destabilizing effects of sudden FPI withdrawals.

The relationship between macroeconomic fundamentals and banking sector performance had long been of academic interest. According to Schaeck and Cihák (2010), macroeconomic stability significantly contributed to the soundness of the banking sector. Their study observes that GDP growth,

inflation control, and stable interest rates are essential for reducing financial fragility.

Macroeconomic fundamentals played a critical role in shaping the performance of the banking sector. Fluctuations in inflation and interest rates directly influenced banks' lending margins, while GDP growth was associated with trends in credit expansion and asset quality. Bernanke and Gertler (1995) introduced the financial accelerator hypothesis, which highlighted the mechanisms through which macroeconomic shocks propagated across financial institutions, amplifying their effects on the broader economy.

Studies by Vithessonthi and Tongurai (2015) have noted that exchange rate volatility, inflation, and money supply growth significantly affect banking sector stock returns across ASEAN economies. In the Indian context, Sharma and Sehgal (2017) analyzed the dynamic relationship between macro indicators and sectoral indices, identifying GDP and interest rates as significant predictors of banking index performance. Misra and Behera (2006) used a structural vector autoregression (SVAR) model to examine the interaction among inflation, interest rates, and financial markets. They have concluded that inflation expectations and real interest rates are statistically significant predictors of market performance, including banking stock indices.

Further, Barrell, Davis, Fic, and Karim (2010) have documented that banking crises are often preceded by rapid credit growth, rising interest rates, and sharp asset price increases—highlighting the role of economic indicators as early warning signals.

Volatility modeling has evolved, to a marked extent, with the development of advanced econometric tools. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later extended by Bollerslev (1986) into the Generalized ARCH (GARCH) framework. These models are widely used in financial economics to study time-varying volatility in asset prices.

Volatility in the banking sector is often linked to both internal and external shocks. According to Mishkin (1999), banking sector instability can amplify economic downturns through credit crunches and deteriorating asset quality. More recent studies such as those by Das and Ghosh (2006) have explored volatility using GARCH models, finding that bank stock returns are significantly affected by monetary policy announcements and market sentiment. Mukherjee and Naka (1995) used a VECM approach to analyze stock prices and macroeconomic indicators, concluding that variables like exchange rate and inflation are cointegrated with market indices. More recent work by Jain and Dhal (2020) has implemented a VAR model to capture the transmission mechanism between capital flows, economic indicators, and financial sector stability.

Kumar (2011) applied a GARCH model to assess the volatility of Indian banking stocks and found a strong association between banking sector volatility and macroeconomic shocks. His work underscores the sensitivity of banking stocks to changes in exchange rates, interest rates, and inflation.

Rangarajan and Pandit (2018) have examined the Bank Nifty Index and observe that banking sector stock volatility is more sensitive to policy-driven events, such as changes in repo rate and statutory liquidity ratios, than to market-wide movements.

Joshi and Ghosh (2013) utilized a Vector Autoregression (VAR) model to analyze the relationship among FPI, stock market returns, and macroeconomic indicators in India. They found evidence of bidirectional causality between FPI flows and market returns, reinforcing the view that FPI is both influenced by and influences domestic financial conditions.

Volatility in the banking sector has been a focal point of financial stability research, especially in emerging markets like India where capital flows are sensitive to both domestic and global macroeconomic conditions. Foreign Portfolio Investment (FPI), in particular, has been shown to be a significant driver of short-term capital market volatility.

Recent studies by the Reserve Bank of India (RBI) suggest that net FPI inflows significantly Granger-cause volatility spillovers across asset classes such as equity, bonds, forex, and gold markets, whereas reverse causality is generally not observed (RBI, 2023a). This highlights the critical role of FPI as an exogenous volatility source rather than a reactive variable.

Macroeconomic and geopolitical uncertainties have also been found to affect volatility patterns in the banking sector. For instance, periods of heightened geopolitical risk—such as the Russia–Ukraine conflict and Middle East tensions—have coincided with volatile capital flows and elevated financial stress indicators, including the VIX and currency fluctuations (RBI, 2023b).

Sen, Mehtab, and Dutta (2021) applied asymmetric GARCH models to Indian sectoral indices and found that banking stocks exhibited greater conditional volatility in response to macroeconomic news and global uncertainty, emphasizing the asymmetric nature of volatility transmission.

Cross-border volatility spillovers were examined by Das and Das (2022), who studied India's interlinkages with G7 countries during the COVID-19 crisis. Their findings indicate that banking sector volatility in India increasingly correlates with international market dynamics during periods of global stress, suggesting a growing exposure to external shocks.

The IMF (2024) reported that global FPI equity holdings surged to a record US $40.2 trillion by mid-2024, reflecting increased portfolio exposure to emerging markets. This trend is mirrored in India, where financial services—including banks—remain a primary destination for portfolio inflows (IMF, 2024; RBI, 2024).

Additionally, composite financial condition indices constructed by the RBI (2023c) using Principal Component Analysis show that variables such as interest rates, inflation, and exchange rates significantly affect banking sector stress and systemic volatility. These findings support the inclusion of macroeconomic indicators as key explanatory variables in volatility models.

These studies underscore the relevance of multivariate approaches—such as GARCH and PCA-based models—for capturing the complex interplay between capital flows and economic fundamentals in shaping banking sector volatility. Despite a growing body of work on financial volatility and capital flows, there remains a paucity of research specifically targeting the banking sector volatility using a comprehensive multivariate framework incorporating both FPI and macroeconomic indicators. This study aims to address that gap and contribute to the understanding of systemic risks in emerging market banking sectors.

While individual studies have explored the impact of FPI or macroeconomic indicators on the banking sector, there remains a lack of integrated, multivariate analyses that jointly assess the influence of both. Most studies also focus on either short-term FPI shocks or long-term economic fundamentals but rarely combine both into a cohesive volatility model. This study aims to bridge that gap by applying a multivariate econometric framework to evaluate the joint impact of FPI and economic indicators on the volatility of the banking sector, particularly in the context of a dynamic emerging economy like India.

Objective of the study

The main objective of this research is to analyze the factors contributing to volatility in the banking sector, with a particular focus on Foreign Portfolio Investment (FPI) and key macroeconomic indicators. More specifically the paper tries to achieve the following objectives:

- To examine the short-run and long-run associations within Banking sector stock market volatility and FPI investment in the Banking sector.
- To analyze the impact of foreign portfolio investment in Banking sector on sectoral returns and volatility of Banking sector stock indices.

DATA AND METHODOLOGY

The official NSDL website is utilized to gather the weekly time series figures on FPI in the selected industry, whereas the National Stock Exchange website is the source of sectoral indicator data. This study specifically examines sectoral indicator.

The study also includes an analysis of macroeconomic variables interest rate, CPI, and exchange rate USD/INR with weekly data sourced from the authorized website of RBI www.rbi.org.in.

The period from April 2012 to March 2023 has been selected for the study. For an eleven-year period, from April 2012 to March 2023, the current study uses weekly time series data from the selected sector's FPI and the Banking sector index from the NSE, as well as data from the VIX, interest rate, CPI, and exchange rate USD/INR. The period of study is covered for 11 years (April 2012 to March 2023).

The study covers the period from April 2012 to March 2023, spanning eleven years. This period was chosen for several reasons. First, it captures multiple phases of economic and financial cycles, including pre- and post-reform policy environments, regulatory changes, and episodes of macroeconomic volatility. Second, the availability of consistent and high-frequency weekly data during this period for key variables—such as Foreign Portfolio Investment (FPI) in the selected sector, the NSE Banking Sector Index, the India VIX, interest rates, Consumer Price Index (CPI), and the USD/INR exchange rate—makes this timeframe both analytically robust and empirically viable. The chosen duration also includes significant events such as the taper tantrum (2013), demonetization (2016), implementation of GST (2017), the COVID-19 pandemic (2020), and the post-pandemic recovery period, thereby providing a comprehensive context to study the interplay between macroeconomic fundamentals and banking sector performance.

This study employed a quantitative econometric approach to analyze volatility in the banking sector, with a focus on the impact of Foreign Portfolio Investment (FPI) and selected macroeconomic indicators. All analyses were conducted using EViews, a statistical software widely used for time series and econometric modeling.

Descriptive statistics were calculated to examine the distribution and basic properties of the dataset, including mean, standard deviation, skewness, and kurtosis.

To confirm the suitability of the data for time-series analysis, Augmented Dickey-Fuller (ADF) Test were performed to determine the presence of unit roots and to assess whether variables were stationary at level or required differencing.

The Granger causality test was applied to assess the directional influence between FPI, macroeconomic variables, and banking sector performance, determining whether past val-

ues of one variable could predict another.

Based on the stationarity and cointegration properties of the variables depending on the results of the Johansen Cointegration Test. GARCH models (Generalized Autoregressive Conditional Heteroskedasticity) were used to model and forecast volatility in the banking sector index, especially when financial return data exhibited heteroskedasticity and volatility clustering.

To ensure the robustness of the model, several diagnostic tests were performed: LM Test for serial correlation and ARCH Test for heteroskedasticity

Analysis and Results

Table 1: Descriptive Statistics of Variables (April 2012 to March 2023)

Description	Nifty Bank	FPI-Bank	USD/INR	CPI	Interest Rate	VIX
Mean	0.002387	183.0052	67.52154	112.0157	6.781707	17.58399
Median	0.003736	55.00000	67.05250	109.0000	6.625000	16.18875
Maximum	0.154003	11519.00	82.92500	147.0000	10.25000	70.38500
Minimum	-0.214024	-13338.00	51.11500	78.00000	4.250000	10.52500
Std. Dev.	0.033517	2987.262	7.290065	18.86615	1.719995	6.036202
Skewness	-0.232574	-0.029880	-0.038886	0.174970	0.007422	3.785484
Kurtosis	7.931492	7.050454	2.482580	1.984106	1.836018	26.32071
Jarque-Bera	585.7964	392.4665	6.547726	27.61175	32.40884	17.58399
Probability	0.000000	0.000000	0.037860	0.000001	0.000000	0.000000

The weekly time series data of the Nifty Bank return and FPI in Banking sector are displayed statistically in Table 1. The examination discovered that the all the series had positive mean values for the whole study period (April 2012 to March 2023). The findings for skewness and kurtosis provided insight into the underlying distributions of the series.

The variables for the study period had positive kurtosis and negative skewness, according to the results.

Considering that the entire the series appears to have high Jarque-Bera values, it is likely that each variable's series deviates to a marked extent, from the normal distribution.

Table 2: ADF Unit Root Test

Null Hypothesis	t-Statistics	P-Value	Hypothesis Accept/Reject	Inference
Nifty-Bank Return Series is not stationary	-23.68940	0.0000	Reject	Nifty-Bank Return Series is stationary
FPI-Bank Series is not stationary			Reject	FPI-Bank Series is stationary
USD/INR Series is not stationary	-1.189792	0.6805	Accept	USD/INR Series is not stationary
CPI Series is not stationary	-0.126022	0.9445	Accept	CPI Series is not stationary
Interest Rate Series is not stationary	-1.334747	0.6148	Accept	Interest Rate Series is not stationary
USD/INR Series is not stationary at first difference	-22.16254	0.0000	Reject	USD/INR Series is stationary at first difference
CPI Series is not stationary at first difference	-26.05023	0.0000	Reject	CPI Series is stationary at first difference
Interest Rate Series is not stationary at first difference	-23.90475	0.0000	Reject	Interest Rate Series is stationary at first difference

To confirm stationarity, the series are examined for a unit root. The presence of a unit root signifies the non-stationarity of the data. Data stationarity is checked using the Augmented Dickey-Fuller (ADF) test. The Nifty Bank and FPI in banking sector series are confirmed to be stationary at level by the ADF test results. The selected macro-economic variables exchange rate, inflation, and interest rate series are non-stationary at level by the ADF test results. At the first difference, the remaining three macro-economic variables exchange rate, inflation, and interest rate series are stationary.

Table 3: Granger Causality Test Banking Sector

Variables	Pairwise Hypothesis	F-Stat	Prob	Decision	Types of Causality
FPI BANK	FPI-BANK does not Granger Cause BANK RETURN	1.37701	0.2532	Accept	Uni-Directional Causality
	BANK -RETURN does not Granger Cause FPI-BANK	11.4273	1.E-05	Reject	
CPI	CPI does not Granger Cause BANK RETURN	1.19133	0.3046	Accept	No Causality
	BANK RETURN does not Granger Cause CPI	0.57379	0.5637	Accept	No Causality
Interest Rate	INTEREST RATE does not Granger Cause BANK RETURN	0.30385	0.7381	Accept	No Causality
	BANK RETURN does not Granger Cause INTEREST RATE	0.37616	0.6867	Accept	No Causality
USD/INR	USD/INR does not Granger Cause BANK RETURN	0.51063	0.6004	Accept	No Causality
	BANK RETURN does not Granger Cause USD/INR	1.04341	0.3529	Accept	No Causality

The pairwise hypothesis of Granger causality among the variables is presented in the Table 3. There is no causal relationship between the variables, as indicated by the acceptance of all but one paired hypothesis. However, the theory that FPI-BANK does not Granger Cause BANK-RETURN is refuted. This suggests that FPI Bank and Bank Return have unidirectional causality, meaning that bank returns cause FPI Bank.

Table 4: Johansen Cointegration Test Banking Sector

Variables		**Number of Hypothesised Equations**	**Maximum EIGEN Value**	**Critical Value at 0.05 Level**	**TRACE Statistic**	**Critical Value at 0.05 Level**	**Prob.**
FPI-BANK	Nifty-BANK	None	218.2796	40.07757	369.6287	95.75366	0.0000
		At most 1	85.60810	33.87687	151.3490	69.81889	0.0000
		At most 2	42.58858	27.58434	65.74093	47.85613	0.0005

Johansen cointegration test applied on banking sector confirmed the presence of atleast two cointegrating vectors and information asymmetries between FPI flows in the Banking sector and Sectoral respective returns.

Table 5: F-Statistic for Heteroscedasticity test (ARCH)

Sectoral Indices	**F Statistic**	**Prob. F (1, 3717)**	**Obs. R squared**	**Prob. Chi-Sqr(1)**
Nifty Bank	317.7362	0.0000	204.7287	0.0000

For Nifty Bank, the LM Statistic is 317.7362 with a p-value of 0.0000, indicating the presence of ARCH effects in the Nifty Bank series. This confirms the presence of ARCH effects in the Nifty Bank series, warranting further testing.

Table 6: Comparison of GARCH/TARCH, EGARCH and Threshold GARCH for Nifty Bank

	GARCH/TARCH (1,1)	**GARCH/TARCH (2,1)**	**EGARCH**	**Threshold GARCH/ GJR-GARCH**
Significant Coefficients	All	All	All	All
ARCH Significant	Yes	Yes	Yes	Yes
SIC	-4.087655	-4.084794	-4.174275	-4.135314
AIC	-4.155994	-4.160726	-4.250207	-4.211246
Log Likelihood	1199.692	1202.048	1227.684	1216.522

From Table 6, it has been observed that EGARCH models fit most accurately based on the significant parameters of Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and Log Likelihood Criteria (LLC) for Nifty Bank. It has also been noted that for EGARCH model all the three criteria's gets fulfilled to finalise the best fit model. It has the least AIC and SIC values and highest LLC.

Nifty Bank- EGARCH Model

Similar to the TGARCH, the exponential GARCH model developed by Nelson (1991) is to capture the leverage effects of shocks (policies,information,news ,incidents and events) on the financial market.

It allows for the testing of asymmetries. With good (bad) news, assets tend to enter a state of tranquility (turbulence) and volatility decreases(increases).

The conditional variance for EGARCH (p,q) model is specified as:

$$\log\log\left(h_t\right) = \varphi + \sum_{i=1}^{q} n_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{i=1}^{q} \lambda_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{k=1}^{p} \theta_k \log(h_{t-k}) \qquad (1)$$

LHS is the log of variance series (h_t), which makes leverage effect exponential rather than quadratic. This ensures that the estimates are non-negative.

φ =constant, n=ARCH effects ,

λ=asymmetric effects and Θ=GARCH effects

If $\lambda_1 = \lambda_2 = \ldots = 0$ the model is symmetric

But if $\lambda i < 0$, it implies that bad news (negative shocks generate larger volatility than good news)

NIFTY BANKING Index Returns =α+ β_1 CONSUMER PRICE INDEX+β_2FPI EQUITY(BANKING)+3EXCHANGE RATE+4VIX+5INTREST RATE… (2)

Table 7: EGARCH Model- Banking

LOG(GARCH) = C(7) + C(8)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +C(9)*RESID(-1)/@SQRT(GARCH(-1)) + C(10)*LOG(GARCH(-1))				
Variable	**Coefficient**	**Std. Error**	**Z-Statistics**	**Prob.**
C	0.001266	0.013034	0.097148	0.9226
CONSUMER PRICE INDEX	0.000624	0.000131	4.744083	0.0000***
FPI EQUITY(BANKING)	1.63E-06	2.67E-07	6.108749	0.0000***
EXCHANGE RATE	-0.001202	0.000278	-4.329436	0.0000***
VIX	-0.000203	0.000134	-1.510459	0.1309
INTEREST RATE	0.002035	0.000626	3.247823	0.0012***
Variance Equation				
C(7)	-0.096178	0.042828	-2.245683	0.0247**
C(8)	0.019969	0.024145	0.827048	0.4082
C(9)	-0.162477	0.015737	-10.32460	0.0000***
C(10)	0.987677	0.005056	195.3656	0.0000***
R-squared	0.060451			
Adjusted R-squared	0.052166			
Durbin-Watson stat	2.073903			
Number of observations	574			

*** is at 1% significance
** is at 5% significance
* is at 10% significance
Source: E-views generated output

MEAN EQUATION

NIFTY BANKING Index Returns =0.001266 +0.000624CONSUMER PRICE INDEX+1.63E-06FPI EQUITYBANKING+ (-0.001202)EXCHANGE RATE(-0.000203)VIX+0.002035INTEREST RATE… .....(3)

The CPI (0.000624), FPI (1.63E-06) and Interest rates (0.002035) coefficient are positive and significant at 1% level of significance respectively. It implies that the CPI, FPI and Interest Rates have a significant impact on Nifty Banking Sector Returns.

The exchange rates (-0.001202), VIX (-0.000203) coefficients are negative. The exchange rate coefficient is significant at 1% level of significance and has significant impact on the Nifty Banking Sector Returns. Sectoral returns are strongly influenced by the industry's FPI.

Variance Equation

The conditional variance for EGARCH (p,q) model is specified as:

$$\log log\left(h_t\right) = \varphi + \sum_{i=1}^{q} n_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{i=1}^{q} \lambda_i\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{k=1}^{p} \theta_k \log(h_{t-k}) \quad (4)$$

φ =constant, n=ARCH effects , λ=asymmetric effects and Θ=GARCH effects log*log*(ht) =-0.096178+

$$\sum_{i=1}^{q} 0.019969\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{i=1}^{q} -0.162477\left[\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right] + \sum_{k=1}^{p} 0.987677 \log(h_{t-k})$$

The C(7)= φ; C(8)= n; C(9)= ; C(10)= Θ

The coefficients of the asymmetric term is negative (-0.162477) and statistically significant at 1% level of significance.

In exponential terms C(9)= $\lambda = e^{-0.162477} = 0.85004$ which indicates that for the Nifty Banking Sector returns bad news has larger effect on the volatility of the stock than good news.

The ARCH effect is 0.019969 and the GARCH effect is 0.987677

The coefficient of ARCH term, is positive but not statistically significant as can be seen from the above table 7. The coefficient of GARCH is positive and statistically significant, which is the GARCH term.

Volatility Persistence = {(0.019969-0.162477+0.987677)/2} <1

Volatility Persistence = {0.845169/2} <1

Since the value is smaller than 1, it implies that the volatility is persistent and clustering because the GARCH coefficient value is higher than the ARCH coefficient value. The Banking industry's FPI is positive and statistically significant at the 1% level, as this table shows. The industry's FPI significantly influences sectoral returns and volatility.

CONCLUSION

This study examined the relationship between Foreign Portfolio Investment (FPI), key macroeconomic indicators, and volatility in the banking sector using multivariate statistical methods. The analysis suggests that banking sector volatility is significantly influenced by fluctuations in FPI as well as by shifts in core economic variables such as interest rates, inflation, GDP growth, and exchange rates.

This study examined the complex relationship between Foreign Portfolio Investment (FPI), key macroeconomic indicators, and volatility in the banking sector by employing robust multivariate statistical techniques. Through the analysis, it was demonstrated that fluctuations in FPI flows significantly impacted the volatility of the banking sector, highlighting FPI's dual role as both a catalyst and a barometer of market sentiment. Specifically, FPI inflows were found to contribute positively by injecting much-needed liquidity into the banking and capital markets, thereby facilitating improved market depth, enhanced pricing efficiency, and greater availability of financial resources for banks and other market participants.

However, the study also revealed that FPI flows introduced considerable vulnerabilities, particularly during episodes characterized by abrupt capital outflows or sudden stops. Such reversals often triggered sharp increases in banking sector volatility, leading to heightened financial stress and reduced investor confidence. These periods of instability were frequently exacerbated by underlying macroeconomic imbalances, including rising inflation, volatile interest rates, fluctuating exchange rates, and uneven GDP growth patterns. The interplay of these economic variables with FPI-induced capital movements underscored the banking sector's heightened sensitivity not only to domestic economic conditions but also to external shocks and global financial market dynamics.

Moreover, the findings suggested that shifts in macroeconomic fundamentals amplified the transmission of volatility within the banking sector, potentially affecting credit availability, asset quality, and overall financial stability. For example, rising inflation and exchange rate depreciation tended to coincide with increased risk aversion among investors and tighter lending conditions within banks, thereby amplifying systemic risk. Conversely, periods of stable economic growth and favorable monetary conditions were associated with dampened volatility and improved sectoral performance.

The study provides comprehensive empirical evidence that the banking sector's volatility is influenced by a multifaceted set of factors, with FPI acting as a critical link between global financial flows and domestic economic variables. This highlights the need for policymakers and financial institutions to adopt integrated risk management approaches

that consider both international capital flow dynamics and the prevailing macroeconomic environment to mitigate risks and enhance sector resilience.

Overall, the study underscored the importance of robust macroeconomic management and regulatory oversight. The findings emphasized that sustained financial sector stability required active monitoring of foreign capital flows and sound economic fundamentals. By identifying these key influences, the research provided valuable insights for policymakers and financial institutions aiming to mitigate risk and build resilience in the banking sector. By identifying the key influences of Foreign Portfolio Investment (FPI) flows and macroeconomic indicators—such as interest rates, inflation, exchange rates, and market volatility—on banking sector performance, this research offers valuable insights for policymakers and financial institutions. The findings highlight the interconnectedness between global capital movements and domestic financial stability, emphasizing the importance of proactive monitoring mechanisms and adaptive policy frameworks. For policymakers, the study underscores the need to strengthen regulatory oversight and develop macroprudential tools that can cushion the banking system from external shocks. For financial institutions, the insights enable better risk assessment and portfolio management by recognizing the economic signals that precede periods of heightened volatility. Overall, the research contributes to a more nuanced understanding of how external and internal variables interact to shape sectoral risk, thereby supporting efforts to build a more resilient and stable banking environment.

REFERENCES

i. Anand, M., & Tiwari, A. K. (2011). Foreign portfolio investment flows and stock market return in India: A study of causality. International Journal of Financial Management, 1(1), 1–7.

ii. Barrell, R., Davis, E. P., Fic, T., & Karim, D. (2010). Bank regulation, property prices and early warning systems for banking crises in OECD countries. Journal of Banking & Finance, 34(9), 2255–2264. https://doi.org/10.1016/j.jbankfin.2010.02.015

iii. Bekaert, G., & Harvey, C. R. (2000). Foreign speculators and emerging equity markets. Journal of Finance, 55(2), 565–613. https://doi.org/10.1111/0022-1082.00220

iv. Bernanke, B. S., & Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. The Journal of Economic Perspectives, 9(4), 27–48. https://doi.org/10.1257/jep.9.4.27

v. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

vi. Das, A., & Das, R. C. (2022). Volatility spillovers between India and G7 countries during COVID-19: A DCC-GARCH approach. arXiv preprint. https://arxiv.org/abs/2208.09148

vii. Das, A., & Ghosh, S. (2006). Financial deregulation and efficiency: An empirical analysis of Indian banks during the post reform period. Review of Financial Economics, 15(3), 193–221. https://doi.org/10.1016/j.rfe.2005.04.006

viii. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007. https://doi.org/10.2307/1912773

ix. Ghosh, A. R., Saidi, R., & Johnson, M. (1999). Who moves the Asia-Pacific stock markets? US and Japan or the regional economies? Asian Economic Journal, 13(1), 72–90. https://doi.org/10.1111/1467-8381.00065

x. Gordon, J., & Gupta, P. (2003). Portfolio flows into India: Do domestic fundamentals matter? (IMF Working Paper No. WP/03/20). International Monetary Fund. https://doi.org/10.5089/9781451844213.001

xi. IMF. (2024, July). Foreign portfolio investment equity holdings hit record high in June 2024. IMF Beta Data. https://betadata.imf.org/en/news/31925

xii. Jain, R., & Dhal, S. (2020). Capital flows and financial sector stability in India: A dynamic VAR analysis. RBI Occasional Papers, 41(1), 35–59.

xiii. Joshi, P., & Ghosh, S. (2013). Foreign capital inflows and financial markets: Evidence from India. International Journal of

Economics and Finance, 5(10), 45–56. https://doi.org/10.5539/ijef.v5n10p45

xiv. Kumar, M. (2011). Modeling volatility of Indian stock market: A comparative study of GARCH and EGARCH mod els. International Journal of Trade, Economics and Finance, 2(3), 232–237. https://doi.org/10.7763/IJTEF.2011.V2.108

xv. Misra, S., & Behera, H. K. (2006). Financial liberalisation and monetary policy in emerging markets: The case of In dia. RBI Occasional Papers, 27(1 and 2), 21–50.

xvi. Mishkin, F. S. (1999). Global financial instability: Framework, events, issues. Journal of Economic Perspectives, 13(4), 3–20. https://doi.org/10.1257/jep.13.4.3

xvii. Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the Japanese stock market: An application of a vector error correction model. The Journal of Financial Research, 18(2), 223–237. https:// doi.org/10.1111/j.1475-6803.1995.tb00563.x

xviii. Rai, K., & Bhanumurthy, N. R. (2004). Determinants of foreign institutional investment in India: The role of return, risk and inflation. The Developing Economies, 42(4), 479–493. https://doi.org/10.1111/j.1746-1049.2004.tb00947.x

xix. Rangarajan, C., & Pandit, V. (2018). Indian economy: Essays on money and finance. Academic Foundation.
Reserve Bank of India (RBI). (2023a). Capital flows and volatility spillovers in Indian financial markets. RBI Work ing Paper Series. https://rbi.org.in/scripts/PublicationReportDetails.aspx?ID=1237

xx. Reserve Bank of India (RBI). (2023b). Geopolitical risk and market sensitivity: Recent trends in FPI flows.
RBI Bulletin, July 2023. https://rbi.org.in/Scripts/PublicationReportDetails.aspx?ID=1269

xxi. Reserve Bank of India (RBI). (2023c). Measuring financial conditions in India: A principal component approach. RBI Bulletin, September 2023. https://rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=21668

xxii. Reserve Bank of India (RBI). (2024). Recent trends in foreign portfolio investments in India. RBI Monthly Bulletin, June 2024. https://rbi.org.in/Scripts/BS_ViewBulletin.aspx?Id=22523

xxiii. Schaeck, K., & Cihák, M. (2010). Competition, efficiency, and soundness in banking: An industrial organization per spective. European Banking Center Discussion Paper No. 2010-20S. https://doi.org/10.2139/ssrn.1607123

xxiv. Sen, R., Mehtab, S., & Dutta, S. (2021). Forecasting sectoral volatility using asymmetric GARCH models: Evidence from India. arXiv preprint. https://arxiv.org/abs/2105.13898

xxv. Sharma, M., & Sehgal, S. (2017). Impact of macroeconomic variables on sectoral indices in India. Business Analyst, 38(2), 187–206.

xxvi. Vithessonthi, C., & Tongurai, J. (2015). The effect of macroeconomic volatility on banking sector development: Evi dence from East Asian countries. International Review of Economics & Finance, 40, 59–70. https://doi.org/10.1016/j. iref.2015.02.005

Factors Affecting Customer Satisfaction: An Empirical Investigation on Online Banking Services

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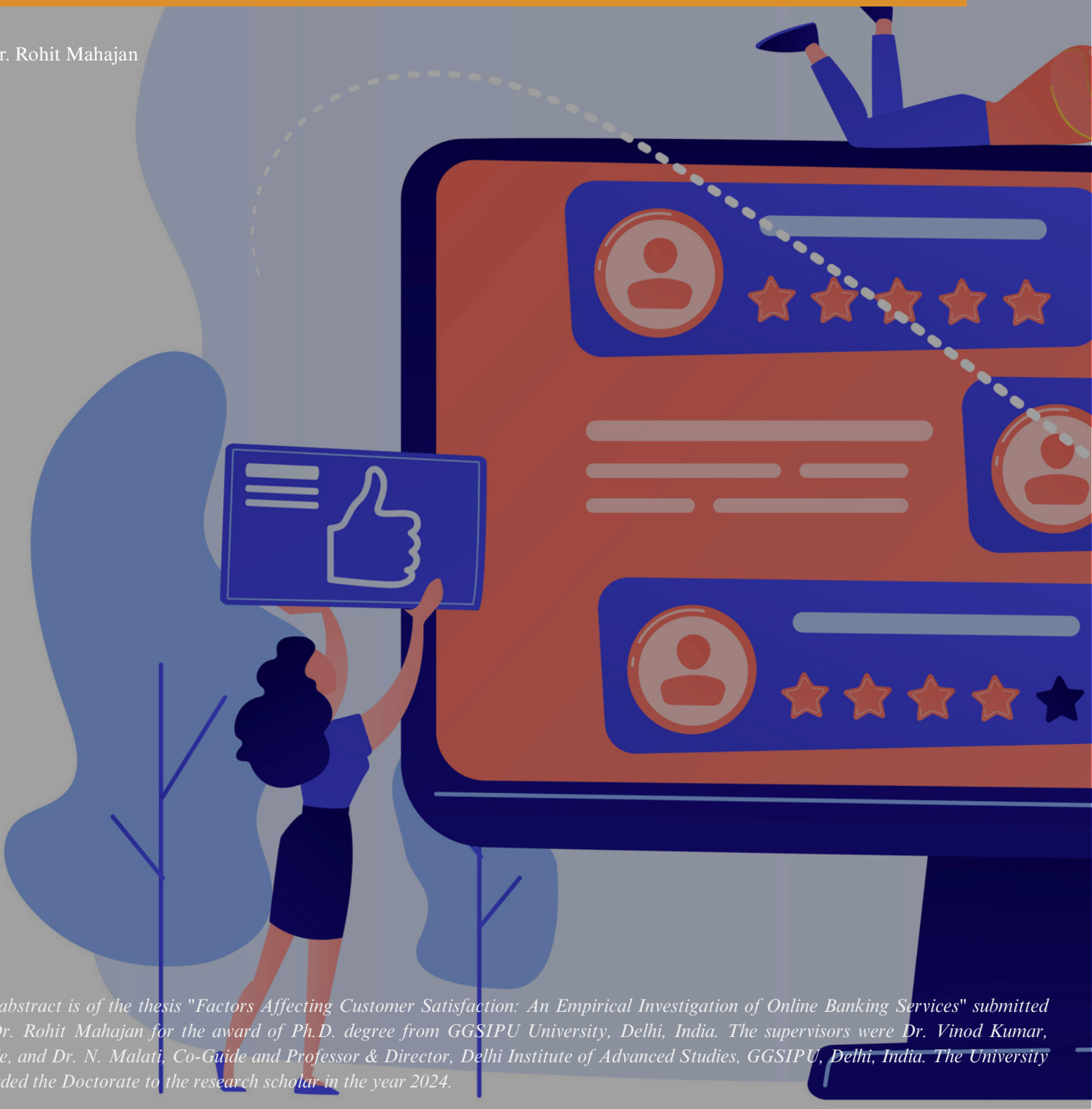

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Abstract

INTRODUCTION

There is no denying, growth & development of electronic technology has resulted in profound change at way of businesses connection to consumers. The adoption of the Internet and technology has been led by banking & non-banking organizations. To define Online banking, one may say that it entails automated distribution of bank assistance to clients directly by electronic means of communication, most notably the Internet. E-banking or PC banking are other names for online banking. Internet banking is described as a "Internet platform, via which users may access various financial services, ranging from making investments to paying bills"(Pikkarainen, Karjaluoto, and Pahnila 2004).

This reform has also been well received by the Indian banking and financial industries. In today's intensely competitive market, more and more Indian banks are attempting to set themselves apart. This not only enables companies to better connect their offers with changing client demands and technological advancements, but it also takes over certain conventional banking duties, resulting in considerable savings in branch-related costs.

As more Indian banks seek to creative techniques, in order to improve the banking experience for customers, institutions have used technologies such as Online banking to make everything easy, Useful and productive, it's more important than ever to assess consumer how customers feel about the service they received in general and how satisfied they were with present online bank services. In addition to assisting banks in developing successful plans to employ efficacy in consumer services as a differentiator for very client-focused sector, estimating customer's satisfactory level may be informative for banking organizations regarding how to retain customers.

By enabling clients to perform their daily personal and professional transactions at their location, online banking is introducing the globe to a new spectrum of banking. Regarding "timeliness and accuracy of information flow," which reduces lag in flow of knowledge a demanding decision-making environment, electronic bank service offers a distinct benefit in comparison to traditional bank branches. According to Venkatesh and Davis, 1996, Model for the Acceptance of New Technologies (TAM) is regarded as popular and reliable paradigm in the field of information system research to forecast an individual's uptake of cutting-edge innovation. This research has proposed and tested an integrated model to account for numerous aspects influencing individual acceptance & usage of online bank service at India adopting "TAM" as a theoretical framework. The model now includes the additional concept perceived risk along with the conventional "TAM" variables perceiving utility and perceived easiness. Trust & website design are the precursors of perceived danger.

Increasing management attention on the important task of providing a protected online space where users may freely share and receive information without fear of reprisal & enable clients to fully utilize online banking is the justification for adding perceived risk into TAM. Risk issues with internet banking services are becoming more widespread worldwide.

Online Banking Services

The way that banking is delivered has fundamentally changed since the middle of the 1990s in favour of self-service options like internet banking. Online banking has gained popularity over the last several years, and now, 55% of clients of private banks in Finland have an agreement with their bank for online banking. As per technical uses, Europe continues to lead the world in online banking. Comparatively, just around 20% of US banks provided online banking services towards the end of 2000, and only 20% of US private banking clients who had access to an internet connection did so (Sheshunoff, 2000; Orr, 2001). About 120 of the top US banks had online banking services by the end of 2002 (Pyun et al., 2002).

As a result, both ATMs and internet banking have encouraged competition among banks in the USA. In this research, "online banking" may be described as web gateway which permits users to access various finance related services, such as bill paying and investing.

Online banking is the automated provision of bank's goods and services to clients directly via electronic means of communication, most notably the Internet. E-banking or PC banking are other names for online banking. Internet banking is described as a "Internet platform, via which users may access various financial services, ranging from making investments to paying bills." This reform has also been well received by the Indian banking and financial industries. In today's intensely competitive market, more and more Indian banks are attempting to set themselves apart. This not only enables companies to better connect their offers with changing client demands and technological advancements, but it also takes over certain conventional banking duties, resulting in considerable savings in branch-related costs.

Service Quality

According to research, quality is determined by how well product and service meets the consumers' need. The discrepancy between what consumers anticipate and what they actually get from the service affects how customers perceive the services' qualities (Parasuraman et al. ,1985). Understanding consumer expectations and tailoring service delivery to meet those expectations has become essential for businesses. The competitive advantage of a firm is increased when it provides exceptional service and meets consumer expectations (Ranganathan and Ganapathy, 2002) .

Customer Perception

Outcome quality and process quality are both included in the term "perception." Other academics have used similar terminology, referring to result quality as what the client really got and process quality as the manner in which the service is provided (Groonroos, 1990). However, since services often have more experience and credibility attributes, it is typically challenging for a consumer to assess result quality for any service (Rushton and Carson, 1989). Customers are prompted by this scenario to consider process quality, meaning that the service is assessed by consumers as it is being delivered (Swartz and Brown, 1989).

Customer Experience

Customer experience has been referenced, debated, and theorised during the last three decades by academics and industry professionals. The word "experience" was first used by pioneering academics, who defined it as fun leisure activities, sensory delights, artistic gratification, and emotional reaction. However, beginning in the late 1990s, marketing experts began to pay attention to customer experience as one of the important streams. Scholars Pine II and Gilmore (1999) and Schmitt were the main ones to start the project (1999). Realizing that actual experiences are different from services is crucial, according to Pine II and Gilmore (1999).

Customer Adoption

Online banking, sometimes known as e-banking, is one e-commerce instrument that the banking sector is embracing Online banking and other IT technologies have improved services for the banking sector. Currently, in this case, "there are" tens of hundreds of online banks websites available worldwide. (Gurau, 2002). Although many industrialised nations, including the United States, have adopted internet banking, States and individuals in Europe, the use of internet banking by banks in emerging nations is also on the rise. (Gurau, 2002). Vietnam is a developing nation that has seen recent tremendous growth (PhanCuNhan, 2005).

However, people must be open to use the technology for internet banking to be effective in Vietnam (PhanCuNhan, 2005). The success of e-commerce, including online banking, ultimately depends on customer attitudes and their willingness to utilise online banking.

Although there has been research with the acceptance of internet bank assistance in the past, numerous research have concentrated upon American nations. Compared to other developed countries, the adoption of the age of internet banking has just begun. Therefore, the goal for this study is to comprehend consumers' perceptions of online banking's acceptability and identify the variables that might predict consumers' desire to utilise internet banking.

Technological Advancements

Many businesses are compelled to implement the necessary technology in Present-day society is replete with sources of age where consumers are the centre of every company in order to satisfy the customers. Technology also facilitates communication between a business and its clients, vendors, and internal stakeholders. This then improves any further contacts with clients, increasing their satisfaction and committed to the business.

From a technology standpoint, CRM is a group of programmes that cater to the requirements of customer-facing operations, which in turn feed into a shared database that is backed by business analytic tools. The endeavor of an organisation to fully use CRM technology will certainly be hampered by ignorance of and disregard for key applications (Eid, 2007). Therefore, it is essential to comprehend the key technological elements that contribute to CRM success.

Online Trust

Trust is defined as "the conviction that one may rely on another's word and that, under unanticipated circumstances, the other would behave in good faith and in the trustor's best interests" (Suh and Han, 2002). By minimising monitoring and legal contracts, trust helps consumers save money and time (Fukuyama 1995) and also offers indicators for the anticipated result (Kumar 1996). Because there are no established assurances that an e-vendor won't participate in damaging positive aspect because the environment is less controlled, trust is a key factor in e-commerce. Numerous experts concur that compared to brick-and-mortar stores or any other channel, e-commerce places a greater emphasis on trust.

Customer Satisfaction

The available research demonstrates the significance of customer satisfaction for long-term company performance (Zeithami et al., 1996). Businesses must outperform rivals to maintain market share and profit by providing high-quality goods and services that satisfy customers (Tsoukatos & Rand, 2006). Oliver (1980) also points out that in order to fully satisfy customers, goods and services must completely fulfil their expectations. Customers are happy when service performance meets or surpasses their expectations. In such case, they are not content (Munusamy, 2006). Additionally, a number of studies define customer satisfaction and dissatisfaction as the judgements of a consumer about the success or failure of a firm to satisfy expectations (Chidambaram, & Ramachandran, 2012, Kheng et al., 2010). When expectations are satisfied, contentment occurs, and when they are not, discontent arises (Oliver, 1980).

According to Lau and Cheung (2013), when consumers anticipate what they feel should happen, they are more likely

to be satisfied than when they experience what they assume to be the opposite perceived performance. Additionally, customer contentment increases the sense of quality and encourages repeat business. The nature of the interaction between consumers and providers of goods and services, in the banking sector especially, is a key component of customer satisfaction. As a result, both the quality of the product and the quality of the service are often seen as crucial requirements and useful factors for maintaining customer happiness. (Muslim & Isa, 2005). It is true that providing clients with high-quality services gives a firm a chance to stand out in a cutthroat industry (Karatepe et al., 2005).

The focus of marketing has been on customer pleasure for more than 30 years (Heitmann et al.,2007). Customer happiness and discontent, according to Patterson et al. (1997), is one of the fundamental marketing ideas that may be linked to any competitive advantage an organisation may have. As a result, every business may gain a competitive advantage over competitors by raising customer satisfaction levels (Mittal and Kamakura, 2001; Patterson et al., 1997). Businesses devote a significant amount of effort to boosting consumer happiness. (Durvasula et al., 2004) because happiness reflects the organization's overall health, its prospects for the future, and offers businesses with several advantages, including increased customer loyalty, reduced customer turnover, lower marketing costs, and improved brand perception (Fornell, 1992). In the current study, the suggested model's dependent variable is chosen to be cumulative satisfaction. Actual experience and anticipation were, however, regarded by Chen et al. (2008) as important determinants of satisfaction. They observed that contentment or discontent is caused by the discrepancy between anticipation and actual experience. Customers who see businesses favourably would rate their satisfaction favourably whereas those who perceive businesses badly would rate their satisfaction negatively. The marketing literature has looked at the connection between client pleasure and experience. According to Zeithaml et al. (2006), experience dominates the assessment process rather than the final result, which is contentment, due to their extensive background knowledge and impeccable reputation, service providers are carefully chosen. Customers are said to be unsatisfied with a service when simply service validity or service dependability are required. Additionally, a service that is very valid but invalid or extremely valid but invalid will result in unhappy clients.

Need for the study

Due to declining customer satisfaction, customer perception, customer adoption and online trust in online banking services, a tool like Service Quality, Customer Experience and Technological Advancements is necessary. Service quality is an antecedent of customer's satisfaction, whether these factors are assessed at the end of a single episode or over the course of several (Oliver, 1993; Spreng & Mackoy, 1996).

Due to its indispensable sequel, customer satisfaction has always been a subject of concern for marketers and practitioners. Although a lot of studies have been conducted over historical context to comprehend the concept of customer satisfaction, the research paradigm is still unable to create a generalized study for the operationalisation of attaining customer satisfaction. A number of different consumer behaviour theories impact how quickly and thoroughly a new service, like online banking, is adopted by the market (M. Sadiq Sohail, B. Shanmugham, 2003). Being mindful of this, the study adopts a relational approach, and characterizes the relationship between service quality, customer experience, technological advancements, customer perception, customer adoption, online trust and customer satisfaction in online banking services.

Research objectives

The present research tries to empirically understand the factors affecting customer satisfaction in the online banking services. For this purpose, the study has established three objectives, which try to encapsulate the essence of the study. The objectives are as follows:

1. To analyze the impact of service quality, customer experience and technological advancements on customer satisfaction in online banking.

2. To analyze the mediating effect of customer perception between service quality and customer satisfaction in online banking.

3. To analyze the mediating effect of customer adoption between customer experience and customer satisfaction in online banking.

4. To analyze the mediating effect of online trust between technological advancements and customer satisfaction in online banking.

REVIEW OF LITERATURE

A literature review examines the published data in a certain field of study during a specific period of time. A review of the literature might consist of a straightforward description of the sources, a recapitulation of the key points, or a reorganization or rearranging of the content. It could provide a fresh interpretation of the outdated information or combine fresh and outdated perspectives to show the subject's intellectual development. The literature review may assess the source and suggest the best course of action to the reader. The review should synthesize, explain, assess, and make the material more understandable. It should be able to specify the kind of research being done and provide a solid theoretical foundation for it.

Customer Satisfaction: Definitions

Customer satisfaction is a person's experience of pleasure or disappointment arising from the comparison of a product's perceived performance (or outcome) in accordance to his or her expectations (Kotler, 2000). Thus, customer satisfaction is a relative notion and is assessed in respect to a standard. At face value, this concept is fairly close to that of perceived quality. Hence, earlier studies have highlighted various conceptual concerns on whether customer happiness and perceived quality are the same or different constructs. Researchers have not always been able to separate these constructs empirically (Dabholkar, 1993; Oliver, 1993).

Dabholkar (1995) observed that the two notions were separate for recent consumers, but they overlapped for long term customers as customer satisfaction assessments become more cognitive with time. Contrarily, other research attempted to distinguish perceived quality and customer pleasure, because the former was defined at the transactional level and the latter at the global level (Eshghi, Haughton, & Topi, 2007). (Eshghi, Haughton, & Topi, 2007).

The level of fulfilment that a company is able to provide for its clients may be measured by customer satisfaction.

The customer's expectations in general and how successfully the organisation has been able to meet those requirements, approach the notion of what a perfect company would be like (Beerli, et. al., 2004).

The level of pleasure a company's consumers feel with their experiences might be interpreted as their plans for the company's future. Service provider, which is determined by the attitude that is developed from the experience of the consumer. When viewed as a whole, there are three distinct types of peripheral segments that may be distinguished:

i) Satisfied customers are the result of a response, either emotional or cognitive.

ii) The response is connected to a specific emphasis (such as a consuming experience, certain expectations, a product, etc.); and

iii) The response takes place at a certain moment (after the decision has been made, after the consumption has taken place, and depending on previous experience, etc). (Kumar, Jumaev and Hanaysha, 2012)

David and Baker (2013) described the concept of customer satisfaction as "an emotional reaction to the gap between what consumers needs and what they receive." Given that internet banking services are readily available.

Customer Perception

Numerous studies have shown that the customer's cognitive evaluation of the firm's offering—which can be thought of as quality as judged by the client is most crucial factor in determining whether or not the customer is satisfied with the product or service and whether or not the customer will remain loyal to the brand (Fornell et al., 1996).

According to Zeithaml (1988), the term "perceived quality" refers to the consumer's perception about an entity's overall excellence or superiority. 178 Journal of Management Research This particular person's experience is characterised by subjectivity, as opposed to the quality that is objective. The study on perceived quality may be traced back to previous studies in services marketing by researchers such as Gronroos (1984); however, until yet, most studies have focused on perceived quality was done in the 1990s (1992, 1994). The SERVQUAL scale, which was established by Parasuraman and colleagues in 1988, is the operationalization for service quality that has received the most widespread recognition.

The term "perceived service quality" refers to an overarching opinion or attitude towards the excellence of the service, whereas "satisfaction" refers to a feeling associated with a particular transaction (Parasuraman et al., 1988).

Service Quality

The quality of the service is comprised of both functional and technical aspects (Gronroos, 1990).

The functional component considers the manner in which the service workers do their jobs, the rate at which the service is provided, and the level of expertise possessed by the workforce. The technical elements are those that are concerned with the final product or service. The SERVQUAL methodology includes consideration of the following five perceived aspects of service quality: tangibles, dependability, responsiveness, assurance, and empathy (Parasuraman et al., 1988). It places an emphasis on the delivery method but does not take the behavioural factors into consideration (Baker and Lamb, 1993; Richard and Allaway, 1993).

According to the findings of research, there are numerous aspects to comprehending service quality. It considers aspects such as the service's physical, interactive, and corporate quality, customer-employee interactions (Rust and Oliver, 1994), and "how" the service was provided (Swartz and Brown, 1989).

Customers will consider a service to be subpar if it does not measure up to the standards, they have set for it (Oliver, 1980).

It has been shown that an improvement in the quality of the service leads to an increase in customer satisfaction, which in turn influences how customers feel about the service provided.

Bahia and Nantel (2000) developed the banking service quality scale as a result of their study on the quality of bank customer service. When it comes to banking, perceived service quality is the outcome of a difference between the customer's expectation and the actual service that is provided. The initial SERVQUAL scale included the majority of the components that make up the marketing mix; however, the "promotion" and "pricing" components were not included (Bahia and Nantel, 2000). The BSQ scale that they established has a total of 31 points, which are broken out as follows: effectiveness and assurance; access; pricing; tangibles; service portfolio; and dependability. According to them, providing exceptional service in banking involves accurately predicting and meeting the requirements and requirements of clients on a constant basis. Therefore, the quality of the service is defined by the views of the consumers, and it should include meeting the requirements of these expectations (Lewis, 1989; Howcroft, 1991; Kathawala and Elmuti, 1991; Blanched and Galloway, 1994; Chen, 2009). Lassar et al. (2000) looked at two factors and found that knowing both was critical for comprehending the quality of bank service. Despite the fact that SERVQUAL played an essential role in quality evaluation, the organisation also considered the functional and technological components of bank services.

Customer Experience

According to the research, the process of creating a positive customer experience is an all-encompassing notion that considers a variety of different transactions, beginning from the moment a client requests a service and ending with his assessment of the quality of that service. Different academics have arrived at distinct definitions for the idea. For example, Sirapracha and Tocquer (2012) proposed that the customer experience is the result of the contact between the customer and the company, which includes the engagement with the employees, self-service technology, service environment, service businesses, and the client themselves. "experience" is described as "a takeaway impression established by consumers experiences with goods, services, and businesses- a perception produced when individuals accumulate sensory information," according to Carbone and Haeckel (1994). (p.9). In the succeeding study, Haeckel et al. (2003) have defined experience to be the sensations that a consumer takes away from an engagement with a firm's products, services, and atmospheric stimuli. This definition may be found in Haeckel et al (2003).'s definition of experience. They put out the idea that contact at different phases of the service delivery process produces hints in the form of emotional and cognitive impressions, which eventually result into experience.

Customer experience dimensions

There is a paucity of empirical backing in the customer experience literature; hence, standardised aspects of customer experience have not yet been defined. In a similar vein, Nigam (2012) came to the conclusion that experiential marketing, also known as sensing, feeling, thinking, acting, and relating on the part of the customer, is significant since it influences the consumer's desire to make a purchase. He proposed that if a consumer had an experience that sticks with them, it would increase their likelihood of making a purchase. On the other side, his desire to buy will drop if he does not have a positive encounter with the product. According to Pine and Gilmore (1998), when an event involves more of a person's senses, it has the potential to be more powerful and memorable.

They were of the opinion that the most important thing for a consumer is to have a positive and memorable experience as a whole. Haeckel et al. (2003) examined the phenomenon from a different angle and identified three distinct sorts of signals that contribute to the customer experience: functional, humanics, and mechanical. They spoke about three different classifications of experience clues: functional, mechanical, and humanic. Functional clues refer to the actual functioning of the product or service; mechanical clues stimulate the emotional circuitry of the brain; and humanic clues are those that evoke affective responses. These three aspects of the client experience may be thought of as separate dimensions. Researchers at Berry et al. (2006) established a connection between functional cues and technical excellence.

The humanic cues include aspects of workers' and service providers' actions and appearances, such as tone of voice, body language, attractiveness, degree of excitement, and so on. The contacts between customers and service providers are very important, and when they contribute to high levels of performance, they may produce an emotional engagement and add to the overall service experience. Last but not least, tangible representations of services are referred to as mechanic hints. According to Berry and Seltman (2007), mechanic cues have the potential to impact consumers before humanic clues and functional clues, and as a result, they contribute to the formation of first-hand expression. Each of these three hints contributes in its own unique way to the overall creation of the client experience.

Backstrom and Johansson (2006) concluded that pleasant experiences are produced when staff are required to go above and above the required service level. This requires the employees to put in more effort. Schmitt's notion that is based on five dimensions is taken into consideration in the research for two reasons since it is in between the two classifications. To begin, these facets constitute the fundamental components that make up the client experience. Second, as was previously said, the customer experience is connected to the whole and accumulated customer experience that is formed throughout the process of learning about, purchasing, and using a product or service (Carbone and Haeckel 1994).

Customer Adoption

A great deal of prior research and studies have been carried out, and a variety of conceptual frameworks have been proposed, in order to ascertain the adoption scenario of IT applications in the market, such as internet banking. The purpose of these studies and frameworks is to identify the factors or determinants that influence the acceptance of technology in the context of the consumer. Since online banking is a kind of technical innovation (Lin and Lee, 2005), research that have already been conducted on the adoption of innovations might be used to the investigation of online banking. The Technology Acceptance Model (TAM) is one of the models that is used by researchers rather often in the investigation of the ways in which individuals accept new forms of technology (Davis, 1989). TAM claimed that the attitude toward adopting new technology can be predicted by using both the perceived utility and the perceived ease of use of the technology. This, in turn, impacts the behavioural intention to use the real system directly. [Citation needed] (Davis, 1989; Venkatesh et al., 2003).visiting to the bank and an improvement in the effectiveness of the system (Rao et al., 2003).

The Technology Acceptance Model (TAM) defines perceived ease of use as "the degree to which the prospective adopter anticipates the new technology chosen to be a free effort regarding its transfer and use" (Davis, 1989). Therefore, the likelihood of consumers making use of the system will increase if they have the impression that using online banking is uncomplicated and does not involve any hassle. TAM was found to be one of the most widely used technology adoption models after Jeyaraj et al. (2006) carried out an exhaustive review of the predictors of technology adoptions by organisations and individuals that were published between 1992 and 2003. This review was based on studies that were conducted between 1992 and 2003.

According to the findings of Jeyaraj et al., TAM is currently used in a significant manner despite the fact that it was originally made available in 1989. (2006). However, a large number of studies claim that TAM by itself is unable to adequately explain users' decisions to adopt new technologies. As a result, the researchers who conducted these studies used TAM as a foundation for their own models and then extended those models by including additional variables that were relevant to the technologies they researched. For instance, Kamarulzaman (2007) used TAM in his research on the adoption of online purchasing. He also added personal and cognitive effect in his analysis. In addition, Amin (2007) made some adjustments to the conventional TAM by integrating perceived legitimacy and the availability of information on mobile credit cards in his investigation of consumers' intentions on the use of mobile credit cards. In addition, the TAM was extended in a number of different ways throughout the course of the research on online banking that was carried out by Pikkarainen et al.

According to Kiong (2004), environmental factors such as the characteristics of a market, which include customers' preferences and demographic factors, could either encourage or inhibit the adoption of e-commerce by businesses. Perceived ease of use refers to the extent to which a person believes that using a system will be free of effort (Davis et al, 1989). "Even if prospective users feel that a specific programme is beneficial, they may at the same time consider that the systems are too difficult to use and that the performance advantages of utilisation are overshadowed by the effort of utilising the application," says the quote (Davis, 1989). There is a great amount of research suggesting that the perception of ease of use has a major influence on attitude, either directly or indirectly via the effect that it has on perceived usefulness (e.g. Davis et al., 1989; Venkatesh and Davis, 1996; Venkatesh, 1999, 2000; Agarwal and Prasad, 1999; Venkatesh and Morris, 2000). TAM demonstrates that PEOU came before PU, and although the former is more of a state, the latter is more of a process. TAM also demonstrates that PEOU is the antecedent of PU (Eriksson, et al., 2005). PEOU conducts the majority of its business via PU since PU can consider both the benefits and the costs of an action. PEOU could be considered a component of the cost (Davis, 1993). Applications that are simple to use are seen as less intimidating by their users (Moon and Kim, 2001), and they are also considered to be of more value to the user. When two information systems have the same functions, the one that is seen as being simpler to use will be regarded as being more helpful. On the other side, if people believe that the system serves no use, then user friendliness won't be enough to drive adoption.

Online Trust

The transactions that take place in online banking involve highly confidential information about clients (Gefen, 2000; Morgan and Hunt, 1994). Because of security flaws and a general lack of confidence in online service providers, people are understandably wary of disclosing sensitive information such as their bank information over the internet (Suh and Han 2002). When it comes to the provision of financial services, the building of trust and confidence is an extremely important factor (Palmer and Bejou, 1994). The formation of trust (such as cognitive-based trust and disposition-based trust) prior to experience ought to have a substantial influence on the customer's intention toward the adoption of online banking. In the context of online banking, the issue of trust is far more significant than it is in the context of traditional banking (Ratnasingham 1998). When it comes to the first phases of a relationship, trust as a belief that we have is highly significant since it provides credit to people before experience. Reichheld and Schefter (2000) stated that this disposition is very crucial when dealing with clients who have little to no experience shopping online.

In the field of marketing, trust has been studied primarily in the context of relational exchanges (also known as relation-

ship marketing). These exchanges can take place between a buyer and a seller (Doney and Cannon, 1997; Ganesan, 1994; Ganesan and Hess, 1997) or between a customer and a provider (Garbarino and Johnson, 1999; Singh and Sirdeshmukh, 2000; Sirdeshmukh et al., 2002). Other researchers have Along with opportunism and happiness, the function of trust in relationships has been conceptualised by a number of researchers as a component of relationship quality (Moorman et al., 1992). (Crosby et al., 1990). It has also been conceptualised as a powerful aspect of relationships (Anderson et al., 1987), a determinant of conflict between parties (Anderson and Narus, 1990), a source of believability and honesty (Zeithaml et al., 1996), and a tool of communication between parties (Anderson and Narus, 1990). [Citations needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed (Mohr and Nevin, 1990). All of these things, in the end, contribute to a solid connection with consumers, which eventually results in increased customer satisfaction and loyalty (Reichheld and Schefter, 2000). Many academics, such as Zaheer et al. (1998), believed that trust was an essential component of a healthy, long-term connection with clients. In a similar vein, Wilson (1995) referred to it as the basic relationship model's core building piece. Finally, Singh and Sirdeshmukh (2000) referred to trust as the "glue" that maintains connections together and makes a beneficial contribution toward CRM and, eventually, the success of organisations.

Technological Advancements

In the prior body of literature, there is a scarcity of studies concerning technological CSFs. Although a wide variety of elements that might impact customer satisfaction (the success of CRM) have been stated in the research, relatively few studies that have been undertaken in the context of CRM give robust statistical evidence. For instance, Turban et al. (2006) emphasised the significance of information systems in order to have a successful CRM deployment. [Citation needed] Umashankar (2001) included the selection of right software as one of the unavoidable aspects for successful CRM implementation.

On the other hand, Lee et al. (2001) noted that the majority of the CRM software that has been built does not even match the most fundamental requirements of customers. This problem also highlights how important it is for a given business to choose the appropriate software for its needs.

Automation of sales forces is yet another important aspect connected to technological advancements (SFA). Since this factor plays such an important part in boosting customer satisfaction, a great number of researchers (Avlonitis and Panagopoulos, 2005; Honeycutt et al., 2005; Morgan and Inks, 2001; Pullig et al., 2002; Rivers and Dart, 1999; Robinson et al., 2005; Speier and Venkatesh, 2002) have shown a keen interest in studying it. Some examples of these studies include Avlon According to Sandoe et al. (2001), businesses should make an investment in the development of their database technologies such as data warehousing and data mining to ensure that customer relationship management (CRM) systems perform correctly, are successful, and achieve their goals. Other researchers have included the internet (Barnes, 2001) and call centres as significant components of the technology-related issues (Wallace and Hulme, 2001). According to findings from Forrester Research, seventy percent of businesses asked feel that contact centre tactics are essential to the success of CRM; nonetheless, many businesses struggle with providing the appropriate information to their consumers.

According to Kirby (2001), these businesses have to realise that CRM cannot operate inside the framework of uncoordinated activities in order for it to be successful.

To improve customer satisfaction and ensure the effective adoption of CRM, businesses need to ensure that all of their tasks are coordinated, and they should also acknowledge the role that technology plays as a facilitator in this process (Hart et al., 2004).

RESEARCH METHODOLOGY

The present research attempts to throw light on the factors which affect the overall satisfaction of the customer towards the banks with special focus on the online banking services. On the basis of an extensive review of literature, this study has identified a few factors that lead to customer satisfaction. Out of those identified a few factors; service quality, customer experience and technological advancements are being treated as the independent variables. The other three factors identified are customer perception, customer adoption and online trust, which act as mediating variables. The last identified variable is customer satisfaction, which acts as a dependent variable. This study tries to establish an inter-relationship between service quality, customer perception, customer experience, customer adoption, technological advancements, online trust and customer satisfaction with different dimensions of Service Quality, Customer Experience & perception and Customer Satisfaction. The current study tries to explore the path from service quality, customer experience and technological advancements to customer satisfaction. For this purpose, a serial mediation path is established starting from service quality leading to customer perception and customer perception leading to customer satisfaction. Further, we also analyse the relationship between customer experience and customer satisfaction which is mediated by customer adoption, and the serial relationship between technological advancements and customer satisfaction which is mediated by online trust.

Rationale of the study

The rationale of this study can be bifurcated into two parts. The first and the basic rationale behind conducting this re-

search is to check the relationship amongst different factors affecting customer satisfaction viz; service quality, customer perception, customer experience, customer adoption, technological advancements, online trust and customer satisfaction in online banking services. An in-depth analysis would help in giving a clear picture as to what ultimately makes the customer satisfaction in online banking services. A question remains whether service quality, customer experience and technological advancements directly relate to customer satisfaction, or if there are other factors that can mediate this relationship. Research done in the past has tried to establish a direct relationship between service quality and customer satisfaction (R. Ragu Prasad, 2018; Rizwan Rheem Ahmed et al., 2017; Debarshi Ghosh et al., 2017), customer experience and customer satisfaction (Mohsen Mazaheri Asad et al., 2016 ; Meenakshi Sharma et al., 2014;

Conceptual Framework

A conceptual framework, depicted in Figure 1, has been designed for the study based on the rationale and objectives. This framework provides a diagrammatic presentation of the actual research work. As shown in Figure 1, service quality, customer experience and technological advancements are independent variables, customer perception, customer adoption and online trust are mediating variables and customer satisfaction is dependent variable.

However, the above-mentioned relationship would be given a more concrete structure only if the inter-linkage is established among them. So, this framework will check the serial mediation among the constructs in this study. This will help in getting a more robust outcome for the study.

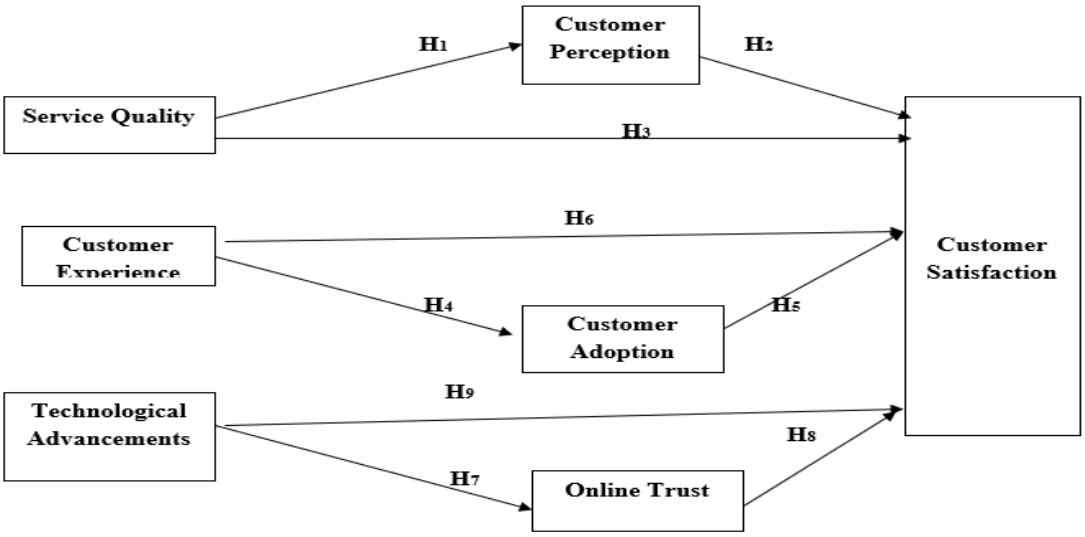

Figure 1 : Conceptual Framework

Hypothesis Formulation

On the basis of the framework discussed, the following hypotheses have been established.

H1: There exists a relationship between service quality and customer perception.

H2: There exists a relationship between customer perception and customer satisfaction.

H3: There exists a relationship between service quality and customer satisfaction.

H4: There exists a relationship between customer experience and customer adoption.

H5: There exists a relationship between customer adoption and customer satisfaction.

H6: There exists a relationship between customer experience and customer satisfaction.

H7: There exists a relationship between technological advancements and online trust.

H8: There exists a relationship between online trust and customer satisfaction.

H9: There exists a relationship between technological advancements and customer satisfaction.

Scale/ Instrument Development/ Questionnaire Design

The current study uses a questionnaire to evaluate the relationship between various customer satisfaction in online banking services related constructs (service quality, customer perception, customer experience, customer adoption, technological advancements, online trust and customer sat-

isfaction).The said questionnaire was divided in two parts, the first section is related to demographic profile of the respondents whereas, the second section of the questionnaire contains measurement statements of various constructs adopted from the previous literature.

Sample Size

The sample size is an essential part of empirical research. The goal is always to draw inference from the population set for the sample. As mentioned previously, the population is viewed to be the sum total of elements that are investigated in terms of time, place, education and unit of sampling. Sample size taken for this study is 728. This number is based on the findings of Orme (1998). According to him, a total sample from 150 to 1,200 respondents was found to be acceptable for joint studies. The total sample of 728 respondents was decided on the basis of the following factors: The present study is a combination of exploratory, descriptive, and causal research.
95% Confidence level required.

Pre-Testing of the Instrument

The purpose of the pilot study was to evaluate the reliability of the measurement items used in the questionnaire. Pilot testing was conducted on a sample of 80 respondents. The said sample size has been decided based on the recommendations of Connelly (2008), where it was suggested to take 10 per cent of the sample projected for the larger parent study. The pilot study also proposed the adjustments to be made in the final questionnaire.

3.8 Reliability Measurement

Reliability is performed to test whether the tools used to measure the variables get a consistent response. Reliability of the scale has been evaluated with the aid of Cronbach's Alpha. A value of 0.7 or more is considered acceptable (Cronbach, 1951; Nunnally, 1978). The overall value of Cronbach's Alpha was computed at .867 thereby, indicating the internal consistency of the items.

Data Collection Procedure

The data, which is primary in nature, has been gathered with the distribution of a structured non-disguised questionnaire. The questions were listed in a pre-arranged order and the respondents were told about the purpose of collecting the information. The research aims to understand the factors affecting customer satisfaction in online banking services. The questionnaire has been circulated in the National Capital Region including Delhi, Ghaziabad, Faridabad, Noida and Gurugram. The questionnaire was circulated through online channels. For the online platform, the questionnaire has been circulated as a Google form on apps such as WhatsApp, Facebook as well as Gmail. Data was collected from July 2021-December 2021. Data has been collected from the respondents who used online banking services. In total, 1000 questionnaires were distributed initially. After removing the un-filled or redundant responses, 728 forms were found fit for statistical analysis: thereby, achieving a 73 percent response rate.

Result and Interpretation

Data Analysis

This section of the thesis offers a precise and detailed report of the analysis as well as the interpretation of the data obtained during the research process. The analysis and interpretation of data is a procedure that attributes value to the information obtained and draws inferences from the gathered information (Spiggle, 1994). It is also known as 'empirical investigation of the organized material', which promotes the discovery of critical knowledge. This chapter concerns the presentation of the findings of the data gathered after the empirical review.

Design for Analysis

The objective behind conducting this research is to study the factors affecting customer satisfaction in online banking services. For this purpose, six variables have been identified, viz. service quality, customer perception, customer experience, customer adoption, technological advancements and online trust. Their independent and inter-relationships will be tested with dimensions customer satisfaction viz; E-SERVQUAL and TAM. The technique of Structural Equation Modeling (SEM) has been used to accomplish the above-mentioned objective. The collected data has been examined with the help of validated tools and techniques. The first step in this procedure was to check for any biasness in the data collected. It has been done with the help of Herman's Single Factor test (Harman, 1967). With no biasness reported in the data, Exploratory Factor Analysis (EFA) has been performed in the SPSS software 24.00. Once the factors were identified using EFA, Confirmatory Factor Analysis (CFA) and Path analysis were used to confirm those extracted factors. The current study will be focusing upon three simple mediating relationships.

Harman's single-factor test for Common Method Biasness (CMB)

As per Podsakoff et al. (2003), common method bias appears to arise when a highly associated measurement scale or maybe related methodology is used in data collection. Harman Single Factor Test has been recommended to test for any biases in the data set (Podsakoff, MacKenzie & Podsakoff, 2012). As per this technique all variables are subject to Exploratory Factor Analysis and if single factor accounts for more than 50 per cent of the variance explained, CMB is presumed to exist (Harman,1976). 43.731 per cent of vari-

ance is explained by a single factor, which is lower than the threshold of 50 per cent (Harman, 1976). Thus, we can infer that the data is free from any biasness.

Craighead et al. (2011) suggested carrying out the CFA, since it offers resilience to the findings of the EFA. Different model fit indices were used for both, a one- factor and a multi-factor model. In the case of a one-factor model, the value of Chi-square, as well as other fit indices, came out to be insignificant, while all values are statistically significant in the multi-factor model. Hence, the multi-factor model is indeed a good fit model, and the single-factor model is not. The difference amongst the model fit indices of both the two models is also significant and exceeds the threshold of 0.001 (Byrne, 2013). It can, therefore, be deduced that the data are not subject to any bias and can be used for further analysis.

Reliability of Measurement Scale

Cronbach (1951) described reliability as "the internal consistency of the measurement scale, which highlights the consistency of the output given by the tool." According to Nunnally (1978), the permissible limit for the measurement scale would be that the Cronbach Alpha value must be higher than the 0.7 cut-off limit. In this study, the value of Cronbach Alpha (α) came out to be 0.933, which comes well within the prescribed limit.

Exploratory Factor Analysis

Using factor analysis, this study extracted 7 factors out of 30 variables. The current study reflects 7 factors representing 30 variables. 84.183 per cent of the variance is explained by the 7 factors and data is being significantly represented (Pett, Lackey & Sullivan, 2003).The eigenvalue of all 7 factors has been determined to be more than 1. The component F1 explains the maximum variance, among 7 factors, with eigenvalue of 9.183 and 43.731 per cent of the variance explained. It is followed by component F2, with eigenvalue of 4.163 and 19.825 per cent of the variance explained. Accordingly, F3; F4; F5, F6, F7 comes next, with eigenvalue of 1.719, 1.415, 1.197. 1.176. 1.857 respectively and 8.185, 6.740, 5.702, 4.876, 4.471 per cent of the variance explained, respectively.

Assessment of Measurement Model Fit

The fitness of the measurement model is evaluated with the aid of AMOS 21 after assessing the validity of the model. This step validates the support of the measurement model for the theoretical structure. Various model fit indices are used in this analysis, and this facilitates the confirmation of the model fit. The values are CMIN(χ2) =401.736, (df)= 179, CMIN/df (χ2 /df) = 2.244 which is lower than the threshold of 4, GFI= 0.938, AGFI= 0.920, CFI= 0.983, IFI= 0.983, NFI= 0.969, and ECVI = 0. 833.The evaluation of the model fit in this study is carried out as indicated by Boomsma (2000). The required limit has been achieved by AGFI, IFI, NFI and CFI. The RMR is 0.063, that is lower than 0.1; the RMSEA has also been shown to be 0.045, which is lower than 0.06. All model fit measures indicate that the model is, indeed, a good fit.

Path Analysis

The direct relationship between independent and dependent variables has been tested before beginning with the mediation analysis. The present research tries to study service quality, customer experience and technological advancements as independent variables (IDV). Customer Satisfaction is Dependent Variable (DV). Two distinct criteria have been utilized to verify the relationship. Firstly, the Critical Ratio (CR) has been compared to the Z-value at the 95% confidence level (C. R > 1.96). Secondly, the regression coefficient has been verified at a 5 % significance level ($p<0.05$).Only once the relationship is proved to be significant, then we can proceed with the testing of hypothesis.

All relationships except customer perception and customer satisfaction, customer adoption and customer satisfaction & online trust and customer satisfaction relationships came out to be significant. The relationship depicting impact of customer perception on customer satisfaction (H2) has been found to be insignificant, as the p-value came out to be more than 0.05, i.e. 0.339. Likewise, the statistical results do not support the relationship as (b= 0.035, p=***); CR (0.955), which is less than the required 1.96 value.

The study also examines the mediating role of customer perception, customer adoption and online trust. This helps in a better understanding of the inter-relationships of factors affecting customer satisfaction.

Mediation Analysis

The mediation analysis aims to clarify the relationship between the predictor, as well as the criterion variable. The predictor variable, indeed, the IDV, while the criterion variable is the DV.

The first indirect effect of service quality on customer satisfaction through customer perception is -.1910. The said effect is negative due to the reason that the bootstrap confidence interval excluded is below zero (-.2021to -.0987). Service Quality leads to higher Customer Perception (0.5745), however, this enhanced Customer Perception was not supported with higher customer satisfaction. The second indirect effect of customer experience on customer satisfaction through customer adoption is 0.0712. The effect came out to be positive owing to the reason that the confidence interval is above zero (.0084 to .1378). Customer Experience leads to higher customer adoption (0.4956), and a higher customer adoption leads to higher customer satisfaction (0.1438). The third indirect effect of technological advancements on

customer satisfaction through online trust is 0.0852. As discussed previously, the positive effect is due the confidence interval being above zero (.0421 to .1366). Technological advancements lead to online trust (0.2452), and a higher online trust leads to higher customer satisfactions (.3476). Hence, based on statistical evidence, it is deduced that the above-mentioned three indirect relationships are significant.

CONCLUSION

Customer Satisfaction is the ultimate objective of every organization. Every organization opts innovative ways for delivering goods or services to its customer to increase their level of satisfaction. Banks are also adopting the latest technology to make the services more secure and convenient for their customers to make them more satisfied.

The study focuses on three broad objectives. First objective was to analyse the effect of service quality, customer perception, customer experience, customer adoption, technological advancements and online trust on customer satisfaction. The said objective has been accomplished for three variables, viz. service quality, customer experience and technological advancements. Service quality significantly impacts customer satisfaction in online banking services. Similarly, customer experience and technological advancements influence the satisfaction level of the customer in online banking services. The relationship between service quality and customer satisfaction is mediated by customer perception, the relationship between customer experience and customer satisfaction is mediated by customer adoption and the relationship between technological advancements and customer satisfaction is mediated by online trust.

The basic premise of the research is based on the analysis of inter-relationship of factors affecting customer satisfaction in online banking services. The current study examines the impact of service quality, customer perception, customer experience, customer adoption, technological advancements, and online trust on customer satisfaction.

Findings of the study revealed that service quality shares a significant relationship with customer perception and customer satisfaction, customer experience shares a significant relationship with customer adoption and customer satisfaction and technological advancements share a significant relationship with online trust and customer satisfaction. Service Quality directly impacts customer satisfaction and indirectly through customer perception (mediating variable), customer experience directly impacts customer satisfaction and indirectly through customer adoption (mediating variable) and technological advancements directly impact customer satisfaction and indirectly through online trust (mediating variable). The results obtained suggest that the customer perception, customer adoption and online trust are central for development of customer satisfaction. Marketers always thrive to satisfy their customers to a large extent. They try to convince customers to use the services offered so that their satisfaction level can be measured accurately.

From the managers' viewpoint, the findings of the study support that service quality exerts a stronger influence on customer perception and customer satisfaction; customer experience exerts a stronger influence on customer adoption and customer satisfaction (Wai-Ching Poon, 2008) & technological advancements exert a stronger influence on online trust and customer satisfaction (M Sadiq Sohail et al., 2003). This implies that if the manager wants to increase the level of satisfaction of customers in online banking services, he should develop strategies to increase the level of perception of customers, the adoption of online banking services and build up the online trust.

The level of satisfaction that Indian clients have had with the service provided by domestic financial institutions is a major factor in determining their views of global banks. There is a significant discrepancy in the service quality in terms of both service delivery and result, and these are critical elements that influence their impressions of international banks provide superior levels of service.

Limitations and Future Scope:

The sample selection of the study is restricted to New Delhi and related areas. Nevertheless, to boost the generalizability of the findings, data from different regions of India could also be collected. In the future, a much larger and more representative response group will allow the researcher to conduct a much more comprehensive analysis, maintaining the efficacy and reliability of the techniques used. In addition, it is possible to perform a comparative analysis between two banking sectors to see which banking sector is more dominant.

REFERENCES

i. Akbar M. M. and Noorjahan P. (2009), "Impact of Service Quality, Trust and customer Satisfaction on Customers Loyalty". ABAC Journal Vol. 29, No. 1 (January-April 2009, pp.24-38).

ii. Bailey, J., & Pearson, S. (1983). "Development of a Tool for Measuring and Analyzing Computer User Satisfaction". Management Science, 29(5), 530-545.

iii. Bauer, H.H., Hammerschmidt, M. and Falk, T. (2005). "Measuring the quality of e-banking portals." International Journal of Bank Marketing, Vol. 23, No. 2, pp. 153-75.

iv. Benamati S. and Serva K. (2007), "Innovation characteristics and innovation adoption implementation: a metaanaly sis of findings'', IEEE Transaction of Engineering Management, Vol. 29, pp. 34-52.

v. Cronbach L J (1951), " Coefficient Alpha and Internal Structure of Tests", Psychometrika, Vol.16, No. 3, pp. 297- 334.

vi. Doll, et al (1995), "Measuring Customer Information Satisfaction for Website Marketing" Journal of Internet Bank ing and Commerce, Vol.9, No.3, pp.33-40.

vii. Featherman T.and Pavlou S. (2002), "Predicting E-Services Adoption", Journal of Online Security, Vol.34, No.2, pp.83-107.

viii. Flavian, C., Torres, E., & Guinaliu, M. (2004). "Corporate image measurement A further problem for the tangibiliza tion of Internet banking services". International Journal of Bank Marketing. Vol. 32 No. 3, pp. 107-125.

ix. Gan, C., Clemes, M., Limsombunchai, V., & Weng, A. (2006). "A Logit analysis of electronic banking in New Zea land". Discussion Paper No. 108, Commerce Division, Lincoln University, Canterbury.

x. Green S, Salkind N and Akey T (2000), Using SPSS for Windows : Analysing and Understanding Data, Upper Sad dle River, Prentice Hall, NJ.

xi. Hair J F, Black W C, Babin B J and Tatham R L (2006), Multivariate Data Analysis, 6th Edition, Prentice-Hall, Englewood Cliffs, NJ. Ibrahim, E.E. (2006). "Customers' perception of electronic service delivery in the UK retail banking sector".

xii. International Journal of Bank Marketing, Vol. 24, No. 7, pp. 475-493. Ives, B., Olson, M., & Baroudi, J. (1983)."The Measurement of User Information Satisfaction". Communications of the ACM, 26, 785-793.

xiii. Jane et al, (2004), "Adoption and Diffusion of Electronic Banking by Customers: Critical Analysis of Empirical Evi dences". International Journal of Financial Management, Volume 1 Issue 1, pp 29-46.

xiv. Kamel H. and Hassan I., (2003), "A study on risk factors of Internet Banking", International Journal of EBanking, Vol.5, No.4, pp.17-22.

xv. Kumbahar V. M. (2010). "Reliability and validity of 'eBankQual' Scale in ATM Service Settings" A Study, in VINI MAYA, Vol. XXXI No. 4 January – March 2011, Published by National Institute of Bank Management, Pune. Laro che M andTaylor T (1988), "An Empirical Study of Major Segmentation Issues in Retail Banking", International Journal of Bank Marketing, Vol. 6, No. 1, pp.31-48.

xvi. Levesque T and McDougall G H C (1996), "Determinants of Customer Satisfaction in Retail Banking", International Journal of Bank Marketing, Vol. 14, No. 7, pp.12-20.

xvii. Liao, Z. and Cheung, M.T. (2002), "Internet-based E-Banking and Consumer Attitudes: An Empirical Study". Infor mation and Management, Vol. 39, pp. 283–295.

xviii. Muylle S. (1998), "Emerging changes in banking sector", Journal of Service Marketing, Vol.39, No.1, pp.37-52.

xix. Pairot R. (2008), "Members' Satisfaction Of Fitness Service Quality : A Case Study Of California Wow Xperience Public Company Limited, Presented In Partial Fulfillment Of The Requirements For The Master Of Arts Degree In Business English For International Communication" At Srinakharinwirot University, October 2008.

xx. Parasuraman A, Zeithaml V A and Berry L L(1988), "Refinement and Reassessment of the SERVQUAL Scale", Jour nal of Retailing, Vol. 67, Winter, pp. 420-450.

xxi. Parasuraman, A and Zinkhan, G.M. (2002). "Marketing To and Serving Customers through the Internet: An Over

view and Research Agenda." Journal of the Academy of Marketing Science, Vol. 30, No. 4, pp. 286-95.

xxii. Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004), "Consumer acceptance of online banking: An extension of the technology acceptance model". Journal of Internet Research, Vol. 52 No. 2, pp. 67-83.

xxiii. Qureshi, T.M., Zafar, M.K and Khan, M.B. (2008). Customer Acceptance of Online Banking in Developing Econo mies. Journal of Internet Banking and Commerce, Vol. 13, No.1, pp. 12-37.

xxiv. Rayport J F and Jaworski B J (2004), "E-Commerce: Security Issues", International Journal of Online Security,Vol. 42, No. 1,pp. 41-57.

xxv. Servon Q. and Kaestner B. (2008), "Internet banking: where does India stand ?", Journal of Contemporary Manage ment, Vol. 2, No. 1, pp. 38-58.

xxvi. Shil N and Das B, (2008), "A study of Customer Satisfaction with Regard to Banking: An empirical of QFD", The Icfain Journal of Management Research, Vol. VII, No. 8, pp. 7-26.

xxvii. Agarwal, R. and Prasad, J. (1997), "The role of innovation characteristics and perceived voluntariness in the accep tance of information technologies", Decision Sciences, Vol. 28 No. 3, pp. 557-82.

xxviii. Agarwal, R. and Prasad, J. (1998), "The antecedents and consequents of user perceptions in information technology acceptance", Decision Support Systems, Vol. 22 No. 1, pp. 15-29.

xxix. Agarwal, R. and Prasad, J. (1999), "Are individual differences germane to the acceptance ofnew information technol ogies?", Decision Sciences, Vol. 30 No. 2, pp. 361-91.

xxx. Agarwal, R. and Venkatesh, V. (2002), "Assessing firm's web presence: a heuristic evaluation procedure for the mea surement of usability", Information Systems Research, Vol. 13 No. 2,pp. 168-86.

xxxi. Ajzen, I. (1991), "The Theory of Planned Behavior", Organizational Behavior and Human Decision Process, Vol. 50 No. 2, pp. 179-211.

xxxii. Al-Gahtani, S.S. (2011), "Modeling the electronic transactions acceptance using extended technology acceptance model", Applied Computing and Informatics, Vol. 9, pp. 47-77.

xxxiii. Alhudaithy, A.I. and Kitchen, P.J. (2009), "Rethinking models of technology adoption for internet banking: the role of web site features", Journal of Financial Services Marketing, Vol. 14 No. 1, pp. 56-69.

xxxiv. Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", Management Science, Vol. 35 No. 8,pp. 982-1003.

xxxv. Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992), "Extrinsic and intrinsic motivation to use computers in the workplace", Journal of Applied Social Psychology, Vol. 22 No. 14, pp. 1111-1132.

xxxvi. Davis, F.D. and Venkatesh, V. (1996), "A critical assessment of potential measurement biases in the technology acceptance model: three experiments", International Journal of Human-Computer Studies, Vol. 45, pp. 19-45.

xxxvii. DeLone, W.H. and McLean, E.R. (1992), "Information systems success: the quest for the dependent variable", Infor mation Systems Research, Vol. 3 No. 1, pp. 60-95.

xxxviii. DePallo, M. (2000), National Survey on Consumer Preparedness and E-Commerce: A Survey of Computer Users Age 45 and Older, AARP, Washington, DC. Gefen, D. and Straub, D. (2000), "The relative importance of perceived ease of use in IS adoption: a study of e-commerce adoption", Journal of the Association for Informa tion Systems, Vol. 1 No. 8, pp. 1-28.

xxxix. Gerrard, P. and Cunningham, J.B. (2003), "The diffusion of Internet banking among Singapore consumers", The In ternational Journal of Bank Marketing, Vol. 21 No. 1, pp. 16-28.

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