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DIAS Technology Review

The International Journal for Business & IT

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ARTICLES

From The Editor's Desk

It gives us immense pleasure to present to our esteemed readers the forty-first issue of the DIAS Technology Review, a scholarly endeavour that continues to reflect the evolving contours of research, innovation, and interdisciplinary inquiry in the domains of management, technology, sustainability, and social sciences.

In the contemporary world of work, shifting employment patterns are redefining organizational and workforce dynamics. The research article "**Defining the Factor Structure of Moonlighting: Implications for the Future Workplace**" offers a timely exploration of the growing prevalence of moonlighting practices. Through empirical analysis using Exploratory Factor Analysis, the study identifies key drivers of this phenomenon and examines its implications for organizational policies, employee commitment, and future labour market structures.

Sustainability remains central to global development agendas. The article "**Charting Path: Sustainable Startups and their Role in Global Sustainability Transitions**" maps emerging research trends and thematic clusters, which highlight the transformative role of sustainable startups while identifying critical challenges related to their funding, regulation, and scalability.

The research article, "**Development of an Early Warning System for Slope Instability in Opencast Coal Mines Using Geo-Spatial AI**" demonstrates the application of artificial intelligence in enhancing safety and decision-making in mining operations.

The different perspectives of behavioral finance have been explored in the research study "**Sentiment-Driven Market Dynamics: Evidence from Google Trends and Indian Stock Indices**", which offers nuanced insights into investor sentiment and market movements in the Indian financial context.

Further, the author of the research "**Traditional Wealth and Asset Management in Indian Households: A Generational Study**" provides insights into generational differences in wealth preservation and financial behaviour, demonstrating how traditional values can coexist with digital adoption and financial literacy to enhance inclusive financial participation.

The Ph.D abstract "**Hybrid Information Theoretic Measures and their Applications in Data Mining**", indicates the advancements in data analytics. The researcher introduces innovative hybrid measures to address uncertainty and complexity in real-world data across diverse application areas.

Collectively, all the contributions in this issue reflect methodological rigour, interdisciplinary relevance, and practical significance. We are confident that this edition will stimulate scholarly dialogue and contribute meaningfully to academic and professional communities.

Regards,

Dr. Anju Batra

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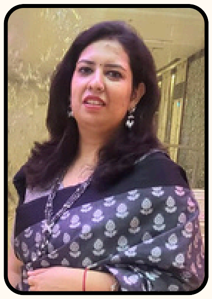

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Defining the Factor Structure of Moonlighting: Implications for the Future Workplace

*Dr. Khushboo Raina, **Ms. Simran Singh, ***Mr. Siddharth Balasubramanyam

ABSTRACT

The practice of moonlighting, where employees hold multiple jobs, has gained traction in recent years across various industries. The practice has recently been highlighted by a prominent IT firm, indicating the necessity of studying this prominent phenomenon in this sector. The practice of long working hours (even remotely) with minimal pay is the reality of many freshers entering this buoyant sector. The "silent" prevalence of this practice is creating a psychological rift amongst employees and necessitates studying the underlying dimensions defining moonlighting. Therefore, to address this gap, this research explores the dimensions defining moonlighting among IT/ITES young professionals. The study was conducted on a sample of 309 working IT/ITES professionals at entry level in MNCs located in Delhi NCR region. Exploratory Factor Analysis using SPSS 29.0 was applied. Four factors viz. perceived role conflict, willful multitasking, growth outlook and risk-reward orientation are explaining 64.6% of variance.

The implications of these findings are discussed in the context of organizational policies, employee commitment, and the broader labor market dynamics. Additionally, the study underscores the growing trend of moonlighting within organizations, with many employees perceiving it as a necessity for financial and professional security. This research provides a foundation for understanding how moonlighting can be defined so as to read the workforce dynamics carefully. . These findings have implications for organizational policies, career development programs, and broader workforce trends in an evolving employment landscape.

KEYWORDS

Moonlighting Intentions, Dimensions of Moonlighting, Sustainable Workforce, Exploratory Factor Analysis, Principal Component Analysis

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INTRODUCTION

Employee moonlighting refers to the practice wherein an individual engages in multiple employment roles concurrently, most commonly involving a primary full-time position supplemented by one or more part-time jobs. Although traditionally associated with holding a single secondary job, the term encompasses any arrangement in which an employee works for more than one organization simultaneously (Jain 2024; Indeed, 2024). The debate on moonlighting garnered widespread attention after a renowned IT firm terminated 300 employees for allegedly working with rival firms while remaining on its payroll. This incident sparked a surge of public discourse, with social media platforms flooded with content bringing the ethical and professional implications of moonlighting into the spotlight (Gupta, 2023). Traditionally seen as a response to financial inadequacies, moonlighting reflects the need for professional development, flexibility, and financial security. This concept has attracted significant attention across different industries, including IT, education, and healthcare, each with its own unique challenges and opportunities (Samaraweera, 2022). Flexibility being the crux of IT sector, favors multiple assignments by employees and results in reduced loyalty (George & George, 2022). However, some organizations view moonlighting as an emerging aspect of the "future of work," especially in light of the increasing challenges in talent acquisition and retention reported by 78% of corporates. In this context, moonlighting is becoming increasingly popular, particularly among millennials and Gen Z professionals who often experience financial insecurity within what they perceive as a "competitive, ruthless, and inadequately supportive" corporate environment (Gupta, 2023).

The rationale behind this behavior is multifaceted. The uncertainty brought by the pandemic made employees seek additional sources of income to safeguard against job loss and economic instability. Many used the extra time gained from reduced commuting to pursue freelance or gig economy opportunities, including roles in content creation, consulting, and online teaching (Hansen et al., 2023; Majumdar, 2022). The increased flexibility in the Information Technology (IT) sector has also led to heightened job insecurity and shorter employment tenures. As a result, individuals are compelled to explore alternative strategies to ensure job stability and secure additional sources of income to maintain financial well-being (Bajpai & Nirwan, 2023). Studies have shown that employees, especially in tech and digital industries, valued flexibility and autonomy more during this period, prompting them to take control of their career trajectories by diversifying income streams (Jain 2024; Bajpai & Nirwan, 2023; Stephen & Stalin, 2023). Saleem (2024) explores how professionals in this industry often moonlight as a hedge against economic volatility and job insecurity. Particularly relevant in periods of layoffs or economic downturns, moonlighting serves as a financial cushion. Dissatisfaction and disengagement with primary employment, coupled with weak HR practices, often lead to employees seeking additional employment opportunities. Moderating effects of commitment and organizational support emphasize that better work environments could mitigate the need for moonlighting (Prasad et al., 2023). Selvam & Selvaraj (2023) argue that moonlighting, particularly in IT and other tech-driven industries, enhance employability and work involvement. By participating in varied roles, employees can develop new skills and expand their professional network. They also suggest that such practices may strain employees' focus on their primary job, leading to performance issues if not effectively managed. Khera (2023) identified how the rise of remote work during the pandemic has provided employees with the flexibility to manage multiple jobs. This, however, raises the questions about the long-term sustainability of such practices, as employees attempt to balance their professional obligations with the demands of multiple jobs. With the rise of the gig economy, increasing job insecurity, and wage stagnation, moonlighting has become a viable option for professionals seeking financial stability in the India's labor market structure (Behera et al., 2024). But divided employee focus, reduced productivity, and potential conflicts of interest can hinder organizational growth and innovation (Tripathy, 2023). Also, moonlighting poses ethical challenges for employers, as it requires balancing employee's autonomy to seek supplementary income with organizational concerns related to potential conflicts of interest, diminished productivity, and compromised employee loyalty.

Despite being so relevant and a current modern workplace dilemma, not many studies addressed the dimensionality of this phenomenon. The study addresses this gap of the published literature and aims to dive deeper into the phenomenon by exploring the dimensions of this construct through EFA (Exploratory Factor Analysis) using SPSS 29.0.

LITERATURE REVIEW

Moonlighting refers to the practice of holding a secondary job or employment, typically at night, in addition to one's primary job (Pryor, 1979). Moonlighting, the practice of employees taking on secondary jobs or freelance work, often to combat boredom, gain extra income, or explore new interests outside their primary employment (Satheeshkumar et al., 2024; Saleem, 2004). The complex interplay between job satisfaction, moonlighting intentions, and organizational commitment is examined by Prasad et al. (2024), whostudiedthemediatingandmoderating effects of HR practices in their empirical study. This research underscores the importance of understanding the psychological and organizational factors that contribute to employee's decisions to engage in moonlighting activities. Selvam & Selvaraj (2023) discuss the concept of moonlighting as a revolution in employability, suggesting that this practice may be viewed as an adaptive strategy in response to changing labor market conditions. The implications of moonlighting in the context of layoffs in the IT sector are explored by Saleem (2024), highlighting the potential risks and benefits associated with this practice in a rapidly evolving industry. Nafeesa (2024) contributes to the literature by investigating the precedents of employee moonlighting intention among private school teachers in Kanchipuram District, providing valuable insights into the factors that drive educators to seek additional employment opportunities. The impact of the COVID-19 pandemic on moonlighting intentions is addressed by Khera (2023), who models the motives behind this practice in the context of the global health crisis, offering a timely perspective on how external shocks can influence employment behaviors. Behera et al. (2024) examined the rise of moonlighting in India, contextualizing this trend within the country's unique socio-economic landscape and labor market dynamics. Laxman Kumar Tripathy (2023) provides an introduction to the concept of moonlighting, exploring its causes and impact on organizational growth, which contributes to a broader understanding of the phenomenon from both employee and employer perspectives. The perception and preferences of IT employees towards moonlighting in the IT industry are investigated by Satheeshkumar et al. (2024), offering valuable insights into a sector where this practice has gained significant attention. (2023) delves into the problems and challenges of moonlighting in the Indian IT scenario, highlighting the complexities and potential conflicts that arise from this practice in a rapidly growing industry. The economic implications of moonlighting are explored by Samaraweera (2022), who examines its impact on earning differentials in Sri Lanka, providing a cross-cultural perspective on this phenomenon. Baby (2024) conducts a comprehensive study unveiling the relationship between employee engagement and moonlighting in the IT and ITES sector, offering insights into how multiple jobholding affects worker's commitment and performance. George (2022) presents a review of moonlighting in the IT sector and its impact, contributing to the growing body of literature on this topic in a specific industry context.

The empirical study conducted employs exploratory factor analysis to identify key dimensions related to moonlighting intentions. These findings contribute to a nuanced understanding of the various dimensions that influence employee's decisions to engage in moonlighting activities, encompassing both individual and organizational factors. The literature review reveals a complex interplay of factors contributing to moonlighting behavior, including financial motivations, career development aspirations, job satisfaction, organizational commitment, andexternaleconomic conditions. The COVID-19 pandemic has added another layer of complexity to this phenomenon, potentially altering employee's perceptions and motivations regarding multiple jobholding. The IT sector emerges as a focal point in many studies, reflecting the prevalence and significance of moonlighting in this industry. However, the research also spans various other sectors, including education and libraries, indicating the widespread nature of this practice across different professions. The ethical implications of moonlighting, its impact on organizational performance, and its relationship with employee engagement are recurring themes in the literature, highlighting the need for a balanced approach in understanding and managing this phenomenon. As the world of work continues to evolve, particularly in the wake of global disruptions like the COVID-19 pandemic, the study of moonlighting becomes increasingly relevant. Future research may benefit from exploring the long-term effects of moonlighting on career trajectories, work-life balance, and overall job market dynamics. Additionally, cross-cultural studies comparing moonlighting practices and perceptions across different countries and industries could provide valuable insights into the global nature of this phenomenon. The growing body of literature on moonlighting reflects its significance as a contemporary workforce issue, warranting continued attention from researchers, policymakers, and organizational leaders alike.

RESEARCH METHODOLOGY

This research initiative explores the dimensionality of Moonlighting Intentions amongst IT/ITeS employees of junior level working in MNCs in India. The study employes a cross-sectional survey design. A self-constructed questionnaire was administered to the employees chosen through convenience sampling. The sample consisted of 309 respondents, ensuring an adequate sample size for factor analysis (Comrey & Lee, 1992). Based on the extensive review of existing literature, focus group and expert consultation, we developed a 17-item questionnaire to assess the dimensions of moonlighting intentions. Items were measured on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). A focus group interview was conducted before finalizing the instrument. 8 IT professionals working at junior level were contacted for the study. A structured interview resulted in item generation. Exploratory factor analysis (EFA) was conducted using SPSS 29.0 to identify the underlying dimensions of moonlighting attitudes. Principal component analysis with Varimax rotation was employed. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used to assess sampling adequacy and factorability of the data.

The 17-item questionnaire was forwarded to the respondents through online mode. The survey was forwarded to around 365 respondents, out of which 309 valid responses were considered resulting in a response rate of 84%. 73% of the respondents were from the age bracket of 23-25 years, 57% were males and 4% had previous work experience of 1-2 years.

DATA ANALYSIS

Exploratory factor analysis (EFA) was applied to generate a list of explanatory factors that underline moonlighting aspirations. By determining the smallest group of descriptive terms that may account for the greatest amount of common variation in the correlation matrix, this method seeks to be as parsimonious as possible (Tinsley & Tinsley, 1987). The long list of items was reduced to a more manageable and useful set of derived items by using EFA.

Kaiser's criterion and Bartlett's test were performed prior to factor analysis (Table 1). The ratio of squared correlations between variables to squared partial correlations was computed using the Kaiser-Meyer-Olkin (KMO) statistics. For factor analysis, a KMO value greater than 0.5 is deemed appropriate (Kaiser, 1974). Bartlett's measure was very significant ($p < 0.001$) and the KMO score in this study was 0.653, suggesting that factor analysis was appropriate for the moonlighting data.

Table-1: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.653
Bartlett's Test of Sphericity	Approx. Chi-Square	334.860
	df	66
	Sig.	.000

By applying EFA, a four-factor solution emerged, which explained 64.6% of the total variance which depicts that these four factors are explaining approximately 65% of the variance.

The eigenvalues for each factor are shown in the Total Variance Explained (Table 2) both before and after extraction, as well as after rotation (Field, 2000). Overall, 12 components were identified, representing all the variables listed. To minimize error variance and focus on common and specific variance, only factors with eigenvalues greater than 1.0 were retained, as shown in the Extraction Sum of Square Loadings. The table also displays the eigenvalues of the factors after rotation. Notably, Factor 1 explains 25.905% of the total variance before rotation. It is common for the first factor to account for a larger proportion of variance compared to subsequent factors. The rotation of the factor axis optimizes the factor structure, and as a result, Factor 1 now accounts for 19.952% of the variance, while the other factors explain 16.3%, 15%, 13.33% of the variance, respectively. The four components taken together explain 64.594% of the variance, offering a thorough grasp of the variables affecting the characteristics that define moonlighting among IT/ITeS workers.

RESULTS

The Rotated Component Matrix (Table 3) presents the factor loadings for each variable on each factor. Following Steven's (1992) recommendation, only items with factor loadings greater than 0.4 are considered for interpretative purposes. The results of the Exploratory Factor Analysis reveal a four-factor solution.

Factor 1. Perceived Role Conflict: This factor captures the psychological and ethical challenges employees face when managing multiple roles. It includes feelings of role overload (e.g., "I feel that working at two designations will create a role overload", loading = .810) and role ambiguity (e.g., "I feel that working at two designations will create a role ambiguity", loading = .799), where employees struggle with balancing and defining responsibilities. Ethical concerns also arise (e.g., "I believe that working at two profiles simultaneously is not ethical, loading = .684), as employees question the fairness of holding multiple designations. These elements highlight the internal conflicts and ethical dilemmas employees encounter with dual employment. The reliability of this factor is 0.759.

Factor 2. Willful Multitasking: This factor reflects an employee's positive, proactive attitude toward engaging in multiple jobs, viewing it to leverage their skills fully and align with career trends. High-loading statements include "I feel working at more than one organization utilizes my capabilities to full" (loading = .782), "I would like to work at two organizations simultaneously even in part-time mode" (loading = .775), and "I feel holding more than one job is the trend of my organization" (loading = .751). Employees who resonate with this factor often see moonlighting as a valuable career choice rather than a financial necessity. The reliability of this factor is 0.76.

Factor 3. Growth Outlook: The Growth Outlook factor captures the professional and personal development opportunities employees perceive from moonlighting. Employees aligned with this factor view dual employment as a way to enhance their network (e.g., “I believe that being a part of two organizations will increase my own network”, loading = .757) and seek additional skill-building opportunities (e.g., “My primary organization does not give me enough opportunities to enhance my capabilities and to work overtime”, loading = .753). For these employees, moonlighting is a forward-looking strategy for career growth. The reliability of this factor is 0.745.

Factor 4. Risk - Reward Orientation: This factor addresses the financial stability and security considerations associated with moonlighting. Statements that reflect this view include “If one of my organizations will pay me good salary and rewards, I will leave the other one” (loading = .807) and “I feel secondary job will act as a backup option in turbulent times” (loading = .773). These employees see moonlighting as a safety net during economic uncertainties, a pragmatic choice that balances financial risk and reward. The reliability of this factor is 0.643.

Table-2: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.109	25.905	25.905	3.109	25.905	25.905	2.394	19.952	19.952
2	2.128	17.730	43.635	2.128	17.730	43.635	1.956	16.297	36.249
3	1.315	10.955	54.590	1.315	10.955	54.590	1.802	15.016	51.265
4	1.201	10.004	64.594	1.201	10.004	64.594	1.600	13.329	64.594
5	.942	7.848	72.443						
6	.778	6.482	78.925						
7	.623	5.192	84.117						
8	.546	4.554	88.670						
9	.454	3.783	92.453						
10	.430	3.585	96.038						
11	.256	2.137	98.175						
12	.219	1.825	100.000						

Extraction Method: Principal Component Analysis.

DISCUSSION

The findings from this study reveal a multifaceted understanding of moonlighting among IT/ITeS professionals, primarily in the early stages of their careers. The four identified factors provide critical insights into the motivations and challenges associated with holding multiple jobs simultaneously. The first factor, Perceived Role Conflict highlights the psychological strain employees experience when juggling multiple responsibilities.

Table-3: Rotated Component Matrix

	Component			
	1	2	3	4
I feel that working at two designations will create a role overload.	.810			
I feel that working at two designations will create a role ambiguity.	.799			
I have a great sense of commitment towards my organization so I don't want to look for another job.	.729			
I believe that working at two profiles simultaneously is not ethical.	.684			
I feel working at more than one organization utilizes my capabilities to full.		.782		
I would like to work at two organizations simultaneously even in part-time mode.		.775		
I feel holding more than one job is the trend of my organization.		.751		
If one of my organizations will pay me good salary and rewards I will leave the other one.			.807	
My primary organization does not give me enough opportunities to enhance my capabilities and to work overtime.			.753	
Future economic downturn is one of the reasons I opted for secondary job.			.639	
I feel secondary job will act as a backup option in turbulent times.				.773
I believe that being a part of two organizations will increase my own network.				.757

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Employees express concern over role overload, ambiguity, and ethical considerations, which are consistent with past research on job strain and ethical dilemmas in moonlighting contexts. This finding aligns with existing literature that emphasizes the internal conflicts employees face when managing two jobs (Prasad et al., 2024; Tripathy, 2023). The second factor, Willful Multitasking, portrays a positive attitude towards moonlighting, where employees see it as an opportunity to maximize their skills and keep up with industry trends. Unlike traditional views of moonlighting as purely financially driven, many respondents view it as a strategic career move, which is reflective of broader changes in workforce behavior post-pandemic (Stephen & Stalin, 2023). Growth Outlook, the third factor, underscores the long-term developmental benefits employees see in moonlighting. Respondents emphasized how secondary jobs offer networking opportunities and skill enhancement, particularly when their primary employment does not fully meet these aspirations. This aligns with contemporary views on moonlighting, where professionals seek roles that contribute to personal and professional growth (Selvam & Selvaraj, 2023). The fourth factor, Risk-Reward Orientation highlights how financial security acts as a significant motivator. Moonlighting serves as a safety net in volatile economic conditions, allowing employees to mitigate risks by diversifying income streams. The pragmatic approach to risk management through secondary employment has been noted in other studies (Behera et al., 2024; Saleem, 2024).

These findings expand the discourse on moonlighting by offering a comprehensive view of the interplay between psychological, financial, and developmental aspects. The results suggest that moonlighting is not just a reactive measure to financial instability but also a proactive strategy for career management.

CONCLUSION AND IMPLICATIONS

This study makes significant contributions by identifying the core dimensions of moonlighting intentions among junior-level IT/ITeS professionals. The four identified factors capture the diverse motivations behind employees' decisions to engage in multiple jobs. These findings highlight that moonlighting is not solely driven by financial necessity but is also linked to personal growth and career strategy. From an organizational perspective, these insights carry important implications. Companies in the IT sector should consider revising their policies to address the nuanced reasons employees engage in moonlighting. Introducing flexible work arrangements, creating opportunities for skill enhancement, and offering competitive compensation packages could mitigate the need for employees to seek additional employment. Organizations could focus on addressing ethical concerns and role ambiguity by fostering a transparent and supportive work environment, which in turn could improve employee retention and reduce the negative impact of moonlighting on job performance. On a broader scale, the research suggests that moonlighting is likely to remain a prevalent practice, particularly in the gig economy and remote work environments. Future studies should examine how moonlighting affects employee well-being, work-life balance, and professional advancement over the long run. Furthermore, a comparative study across several industries and geographical areas will offer insightful information about the ways in which cultural and economic factors impact moonlighting practices. The results highlight how businesses and workers must adjust to changing workforce dynamics, where keeping several jobs is becoming more and more viewed as a strategic decision rather than a need.

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Charting Path: Sustainable Startups and Their Role in Global Sustainability Transitions

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ABSTRACT

This study investigates research trends on sustainable startups and their alignment with SDGs, emphasizing dominant themes, influential contributors, and knowledge gaps. A bibliometric analysis of 509 articles (2015–2025) from Scopus and Web of Science using RStudio Biblioshiny and advanced mapping techniques. Results reveal rapid growth, fragmented collaborations, European and Asian leadership, and thematic clusters on innovation, circular economy, digital transformation, and social inclusion.Innovative business models, cross-sector partnerships, and policy environments that encourage green innovation and market growth are some of the things that help sustainable startups succeed. But they still have to deal with big problems, like not being able to get enough funding, not knowing what the rules will be, and the high cost of sustainable technologies that make it hard to use them on a large scale and have a long-lasting effect. Offers one of the first integrated bibliometric mappings of sustainable startups and SDGs, consolidating fragmented scholarship and suggesting future research directions. Restricted to English-language articles indexed in Scopus and Web of Science, potentially excluding relevant regional or non-indexed contributions. Provides actionable insights for policymakers, investors, and entrepreneurs to strengthen collaboration, inclusivity, and digital transformation in sustainable startup ecosystems. Underscores sustainable startups as transformative agents tackling inequality, climate change, and digital exclusion while advancing systemic progress toward the SDGs.

KEYWORDS

Sustainable Startups; Sustainable Development Goals (SDGs); Agenda 2030; Research Trends

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INTRODUCTION

Sustainability has become a central concern in contemporary business and policy debates, driven by global challenges such as climate change, resource depletion, and widening social inequality (Elkington, 1997; Rockström et al., 2009). Within this context, sustainable startups represent a new generation of entrepreneurial ventures that embed environmental and social responsibility at the very heart of their business models. Unlike traditional startups, which are primarily focused on rapid growth and profit maximization, sustainable startups strive to balance profitability with a positive social and environmental impact (Cohen & Winn, 2007; Schaltegger & Wagner, 2011). They often leverage innovation, technology, and circular business practices to develop solutions that address urgent global issues while maintaining economic viability (Bocken et al., 2014).

The importance of sustainable startups lies in their agility and transformative capacity. In 2025, the global ecosystem has witnessed over 16,400 sustainability startups, with increasing activity in regions like the US, Europe, and India (Startups Insights, 2025). These ventures pioneer sustainable products, services, and business models that larger, more established firms may hesitate to adopt (Dean & McMullen, 2007). For instance, in India, a major shift towards sustainability-first startups is evident, with innovators like Desolenator using solar-powered desalination to provide clean water, and Loopworm revolutionizing agriculture through insect- based protein for animal feed (NetZero India, 2025). Globally, venture funding for sustainable technology startups reached approximately $314 billion in 2024, growing steadily from previous years as investors prioritize ventures that demonstrate both environmental impact and financial viability (Souza et al., 2024).

Beyond economic growth and job creation, sustainable startups act as catalysts for systemic change in consumption patterns, industry practices, and community well-being (Hall et al., 2010). Their activities contribute directly and indirectly to multiple United Nations Sustainable Development Goals (SDGs) (United Nations, 2015). Examples include startups advancing renewable energy (SDG 7), zero hunger through sustainable agriculture (SDG 2), good health and well-being (SDG 3), quality education (SDG 4), and responsible consumption and directly to multiple United Nations Sustainable Development Goals (SDGs) (United Nations, 2015). Examples include startups advancing renewable energy (SDG 7), zero hunger through sustainable agriculture (SDG 2), good health and well-being (SDG 3), quality education (SDG 4), and responsible consumption and production (SDG 12) (Muñoz & Cohen, 2018). The European Institute of Innovation and Technology-supported startups alone are collectively valued over EUR 71 billion due to their impact on sustainability, reflecting the rising economic and societal relevance of these ventures (EIT, 2025). In addressing global interest in this topic, we are seeking answers to these research questions.

Research Questions

1. Which authors, institutions, countries, and journals are the most prolific and influential in contributing to the field of sustainable startups and their alignment with the Sustainable Development Goals (SDGs), as measured by bibliometric performance indicators such as publication output, citation impact, and collaboration networks?

2. How can the intellectual foundations, thematic structures, and evolving research fronts of the literature on sustainable startups and SDGs be analyzed through advanced bibliometric techniques, including co-citation analysis, keyword co-occurrence, and thematic clustering, in order to map current knowledge and highlight future research directions?

3. What are the success factors and challenges faced by sustainable startups?

Despite this growing recognition, current research on sustainable startups and their role in the SDGs remains fragmented across entrepreneurship, sustainability science, and innovation management disciplines (Klewitz & Hansen, 2014). There is a pressing need to consolidate this literature, identify dominant research streams, and uncover underexplored areas. Bibliometric analysis provides a valuable method to systematically map research trends, influential authors, networks, and knowledge gaps in this field (Donthu et al., 2021). This study on bibliometric insights into sustainable startups and the SDGs is thus highly relevant, offering valuable guidance to academics, policymakers, investors, and entrepreneurs who aim to leverage innovation ecosystems for sustainable development impact.

DEVELOPMENT IN THE CONCEPTUAL FRAMEWORK

Sustainable Startups

A startup is a company incorporated within the last 10 years, with a turnover below Rs. 100 crores, not formed by splitting an existing business. It focuses on innovation and scalable growth to create wealth and employment. However, sustainable startups have attracted increasing attention in the global economy, highlighting a growing concern with sustainable development and the search for innovative solutions to tackle environmental challenges. Sustainable startups are those that integrate environmental, social, and governance (ESG) practices into their business models, seeking not only profit but also a positive impact on society and the environment (Martins de Souza, Puglieri, and de Francisco, 2024; Butkouskaya, et.al 2020; Tunçalp and Yıldırım, 2022). Startups known for their creativity, agility, and ability to disturbance have thus become indispensable in accelerating the change to sustainability (Veleva, 2021; Bocken, 2015). Startups usually lead in creative ideas to solve difficult social and environmental problems in development and implementation. Their main drivers of sustainable innovation are their ability to test creative technologies, resource management strategies, and business plans. Fields including social impact, sustainable agriculture, renewable energy, and the circular economy (Silvestre and Ěîrcă, 2019) especially clearly show that Startups in these sectors are developing and implementing innovative business ideas and technologies directly supporting some SDGs to be achieved. Startups in the renewable energy sector, for example, are developing innovative forms of energy storage systems, wind turbines, and solar panels in accumulation to come up with creative business plans for financing and distribution renewable energy, known as sustainable startups (Cordova & Celone, 2019). These developments improve the availability of reasonably priced, environmentally friendly energy sources, so benefiting SDG 7 (Affordable and Clean Energy). Sustainable startups are demonstrating that economic growth and sustainability can coexist and help one another by including the SDGs in their corporate plans (Romero et al., 2022).

Sustainable Development Goals (SDGs)

The Sustainable Development Goals (SDGs), adopted by all United Nations member states in 2015 as part of the 2030 Agenda for Sustainable Development, represent a significant evolution in global development paradigms. The SDGs grew from the earlier Millennium Development Goals (MDGs), which were launched in 2000 with a target deadline of 2015 (Sorooshian, 2024). While the MDGs served as a pioneering global framework focused primarily on poverty reduction and basic human development, they were limited in scope and often critiqued for their focus on developing countries without sufficient consideration of environmental sustainability or post-2015 challenges (Hezri, 2013; Ruhil, 2015). Subsequently, a broader global consensus emerged recognizing the need for a more comprehensive and universally applicable agenda that addressed not only poverty and health but also economic growth, environmental protection, and social inclusion.

This consensus culminated in the 2030 Agenda, which substantially expanded the agenda from eight MDGs to 17 SDGs. The range, ambition, and integrated nature of the SDGs mark a paradigm shift towards a holistic understanding of sustainability that incorporates economic,social, and environmental dimensions (Costanza et al., 2016). Crucially, the SDGs attempt to balance these dimensions with the recognition that sustainable development requires simultaneous progress on multiple fronts and across all countries, not just the developing world. This ambitious agenda is indicative of the global community's recognition that fragmented approaches are inadequate, necessitating a framework that promotes integrated development strategies and international cooperation to address complex, interrelated challenges (Pedersen et al., 2023). The evolution from the MDGs to the SDGs thus reflects an important transition from a developmental agenda focused on poverty reduction to a universal, inclusive call for transformative change.

Sustainable Startups and Sustainable Development Goals (SDGs)

Sustainable startups are vital actors in achieving the SDGs because they contribute innovative solutions that can be scaled rapidly to meet diverse development needs (Cordova & Celone, 2019; Eichler & Schwarz, 2019). Their entrepreneurial nature equips them with the flexibility to experiment with novel technologies, business models, and social approaches that address multiple SDG targets simultaneously. For instance, a sustainable startup developing affordable solar-powered water purification systems can simultaneously contribute to SDG 6 (Clean Water and Sanitation), SDG 7 (Affordable and Clean Energy), and SDG 13 (Climate Action) (Küfeoğlu, 2022; Rumbayan et al., 2025). The ability of startups to adapt and iterate on their products and services enables them to respond agilely to complex local and global sustainability challenges.

Furthermore, sustainable startups often catalyze systemic change by demonstrating viable business models that integrate social and environmental responsibility with profitability. This can inspire and influence larger corporations and policy frameworks to adopt sustainability principles more broadly (Souza et al., 2024; Voinea et al., 2019). Their embeddedness in local ecosystems allows them to promote social inclusion and community empowerment, directly supporting goals related to poverty eradication, gender equality, and quality education (Eang et al., 2022; Ghauri, 2022). Hence, sustainable startups not only drive innovation but also embody the practical enactment of SDG aspirations through entrepreneurship, positioning them as indispensable agents in the global sustainability transition.

Evolution of theories

Theory evolution provides a solid foundation for understanding how sustainable startups align with SDGs. Since Rogers' Innovation Diffusion Theory (1962), new ideas have spread and been adopted, explaining how startups scale long-term solutions across markets and societies. Startups increasingly collaborate with governments, investors, and communities to solve problems, which aligns with SDG 17 on partnerships and Stakeholder Theory (Freeman, 1984). Startups that prioritize profitability, inclusivity, and environmental responsibility follow the Triple Bottom Line (Elkington, 1997), which integrates economic, social, and environmental performance. Sustainability Transitions Theory and the Multi-Level Perspective (Geels, 2002) view startups as niche innovators disrupting established systems to accelerate sustainability, while Social Entrepreneurship Theory (2000s) views startups as mission-driven enterprises addressing social and environmental issues, particularly poverty reduction (SDG 1) and gender equality (SDG 5). According to Ecological Modernization Theory (2000s), economic growth and environmental protection can coexist, encouraging startups to adopt eco-innovations and circular business models. Finally, the Resource-Based View (Barney, 1991) and Dynamic Capabilities Theory (Teece, 2007) explain how startups adapt to institutional pressures and global sustainability norms to gain a competitive advantage and achieve sustainability goals. These interconnected theories explain how sustainable startups emerge, innovate, and scale to drive SDG-aligned systemic change.

RESEARCH METHODOLOGY

This paper uses RStudio (Biblioshiny) (version 4.4.2) to perform bibliometric analyses using the Scopus and Web of Science databases. Grijalva et al. (2019) propose that the methodological process is comprised of four phases: Planning, Selection, Extraction, and Execution, with the goal of achieving transparency and clarity (Rashid L. 2019).

Planning

According to Valverde and Llorens (2019), the first phase, which corresponds to planning, is the most pertinent activity. Selecting the primary international scientific databases is an integral part of the planning process. We selected the databases Scopus and Web of Science due to the high level of research and quality there (Pranckutė, R., 2021; Singh et al., 2021).

Selection

Selection is the subsequent step after planning. It is made by the following search string was employed in both databases to conduct a thorough search:

TITLE-ABS-KEY ("sustainable startups" OR "sustainable entrepreneurship" OR "sustainable business" OR "green startups" OR "eco-startups" OR "sustainability-oriented enterprises" OR "MSMEs" OR "SMEs" OR "Small and Medium Enterprises" OR "entrepreneurship" OR "new ventures") AND ("SDG" OR "Sustainable Development Goals" OR "Agenda 2030") AND ("success factors" OR "factors of success" OR "enablers" OR "drivers" OR "barriers" OR "challenges")

Extraction

Inclusion criteria were implemented during phase 2, which encompassed the following:

1. Data is searched on 22 August 2025, temporal range between 2015 and 2025

2. Subject areas selected in Scopus and Web of Science: - Business, Management and Accounting, Social Sciences, Economics, Econometrics and Finance, Environmental Science, Environmental Sciences Ecology, Business Economics, Social Sciences Other.

3. Only Articles that are in the English language

Figure 1 illustrates the flow chart of the research methodology.

Execution

The fourth and final phase entails carrying out the findings from the 509 relevant potential primary studies. The analysis is done through RStudio, which offers the most prolific and influential authors, institutions, countries, and journals contributing to the field of co-citation analysis, keyword co-occurrence, and thematic clustering, in order to map current knowledge of sustainable startups and their alignment with the Sustainable Develop ment Goals.

FINDINGS

Annual Scientific Production

Figure 1 shows the annual scientific production. It is evident from the growing scholarly output between 2015 and 2025 that scholars are becoming more interested in the intersection of sustainability, startups, and the Sustainable Development Goals (SDGs). Research output was limited in the early years, suggesting that sustainability-led entrepreneurship was still developing as a research focus. Nonetheless, there has been a consistent increase in publications since 2018, indicating that academics have started to acknowledge startups as important forces behind accomplishing SDG targets through innovation, green business models, and equitable economic growth. Sustainability has emerged as a fundamental lens for researching entrepreneurial ecosystems, particularly in connection with climate action, responsible consumerism, and sustainable sector development, as seen by the apparent peak in recent years. This increasing tendency demonstrates that sustainability-focused businesses are now regarded as essential tools for implementing the SDGs locally and globally, which is why this sector of study and business is growing quickly.

Most Relevant Sources

The figure 2 highlight the most important sources for business practices and sustainability studies, which is essential for comprehending sustainable startups. Sustainability has the most papers (85), followed by Journal of Cleaner Production (23) and Sustainability (Switzerland) (18). In addition, Cogent Business and Management (12), Business Strategy and the Environment (10), Corporate Social Responsibility and Environmental Management (8), Sustainable Development (7), Technological Forecasting and Social Change (6), Emerald Emerging Markets Case Studies (6) are important sources. The interdisciplinary character of sustainable startups research is highlighted by this distribution, which connects corporate strategy, innovation and sustainability science The interdisciplinary character of sustainable startups research is highlighted by this distribution, which connects corporate strategy, innovation, and sustainability science while emphasizing how startups can act as catalysts for systemic change in line with the UN Sustainable Development Goals.

Most Cited Articles

Table 1 presents the most cited articles in the dataset, highlighting influential contributions that shape the discourse on sustainability, innovation, and business models. The most cited work is by Schot et al. (2018) in Research Policy with 1,183 citations, which shows frames of innovation include Di Vaio et al. (2020) on artificial intelligence and sustainable business models (769 citations) and Bican et al. (2020) on digital transformation in the sustainability context (299 citations). Several articles published in the Journal of Cleaner Production and Sustainability (Switzerland) also feature strongly, underscoring journals as central outlets in the field. Collectively, the most cited papers emphasize themes of innovation systems, digitalization, circular bioeconomy, entrepreneurship, and the role of business models in advancing the Sustainable Development Goals, reflecting the multidimensional nature and global relevance of the research domain.

Primary Information

Table 2 provides the primary bibliometric information extracted from the selected databases. The dataset covers the period from 2015 to 2025 and includes 509 documents published across 261 different sources. The field demonstrates a strong growth trajectory with an annual growth rate of 43.25%, and the average age of documents (2.17 years) indicates that research is relatively recent and contemporary. On average, each document has received 18.86 citations, reflecting a moderate impact in the academic community. The thematic scope of the literature is wide, as reflected in 1,884 author-provided keywords and 1,035 Keywords Plus. Authorship patterns reveal significant collaboration, with 1,640 contributing authors, an average of 3.39 co-authors per document, and only 52 single-authored papers. Moreover, international collaboration is evident, with 22.2% of documents co-authored across countries. Collectively, these indicators highlight the rapid growth, diversity, and collaborative nature of research in this field.

Average Citation per year

Figure 3 shows the average citation from 2016 to 2025. It demonstrates how research on sustainable startups and their connections to the SDGs has evolved. Between 2016 and 2017, citations increased steadily, indicating that academics are becoming more interested in corporate sustainability. In 2018 citations above 16 indicate a significant increase in interest, which is likely due to policy talks and new sustainable startups models. Citations decreased after 2019, with variations continuing into 2020-2021, indicating that early

Table 1. Most Cited Articles

Authors	Journals	Titles	Citations
Schot J, et al. (2018)	Research Policy	Three Frames For Innovation Policy: R&D, Systems of Innovation and Transformative Change	1183
Di Vaio A, et al. (2020)	Journal of Business Research	Artificial Intelligence And Business models in the Sustainable Development GoalsPerspective:A Systematic Systematic Literature review	769
Bican Pm, et al. (2020)	Sustainability (Switzerland)	Digital Business Model, Digital Transformation,Digital Entrepreneurship: Is there a Sustainable "Digital"?	299
D'amato D, et al. (2020)	Forest Policy and Economics	Towards Sustainability? Forest-Based Circular Bioeconomy Business Models in Finnish SMEs	265
Rahdari A, et al. (2016)	Journal of Cleaner Production	Achieving Sustainability Through Schumpeterian Social Entrepreneurship: The Role of Social Enterprises	210
Govindan K, et al. (2020)	International Journal of Producion Economics	Achieving Sustainable Development Goals Through Identifying and Analyzing Barriers to Industrial Sharing Economy: A Framework Development	198
Morioka Sn, et al. (2017)	Journal of Cleaner Production	Transforming Sustainability Challenges Intocompetitive Advantage: Multiple Case Studies Kaleidoscope Converging Into Sustainable Business Models	196
Horne J, et al. (2020)	Journal of Cleaner Production	Exploring Entrepreneurship Related to the Sustainable Development Goals Mapping New Venture Activities With Semi-Automated Content Analysis	135
Schaltegger S, et al. (2018)	International Journal of Entrepreneurial Venturing	Collaborative Entrepreneurship for Sustainability Creating Light of the Un Sustainable Development goals	132
Surana K, et al. (2020)	Technological Forecasting and Social Change	Strengthening Science, Technology, and Innovation-Based Incubators to Help Achieve Sustainable Development Goals: Lessons From India	115

Note: compiled by the author

Table 2: Primary information from the Databases.

Description		Description	
Main information	**Results**	**Authors**	**Results**
Timespan	2015:2025	Authors	1640
Sources(Journals,Books, etc)	261	Authors of single - authored docs	52
Documents	509	Single-authored docs	52
Annual Growth Rate %	43.25	Co-Authors per Doc	3.39
Document Average Age	2.17	International co-authorships %	22.2
Average citations per doc	18.86	Articles	509
References	0		
Keywords Plus (ID)	1035		
Author's Keywords (DE)	1884		

Note: compiled by authors using RStudio

themes had reached saturation or that the focus has changed. After 2022, the trend levels out, and by 2025 it has reached its lowest point. This trend demonstrates how sustainability discussions have broadened into other research areas by integrating sustainable startups into bigger discussions on innovation, the circular economy and the global SDGs. This reflects initial enthusiasm followed by academic diversity.

Bradford's Law

Bradford's Law Fig. 4, which groups journals according to output, demonstrated that the majority of research on sustainable startups comes from a small number of extremely productive sources. In this figure, a long, flat tail follows the Bradford plot's steep beginning curve, showing that the majority of articles are produced by a small group of journals. The primary journal, Sustainability, followed by the Journal of Cleaner Production and Sustainability (Switzerland), serves as the main academic hub. Journals such as Cogent Business and Management and Business Strategy and the Environment do contribute, though not as often. This distribution shows that a small number of core sources are home to the majority of influential research on sustainable startups, making them important venues for expanding our understanding of sustainability-driven innovation and creativity.

Most relevant Authors

With evident relevance to the study of sustainable startups, Figure 5. showcases the most active and relevant authors who have contributed to sustainability and sustainable business practices. The leading authors with four publications each, like Abdelwahed N, Lim W, and Wang S, shows that they are actively engaged and influencing this field. They are followed by Abbas A, Fuentes-Moraleda L, García-Muiña F, Günzel-Jensen F, Kim E, Korsgaard S, and Kratzer J, each of whom has three papers that shows a constant level of intellectual engagement. The existence of several authors with comparable contributions highlights the growing scholarly interest in entrepreneurship, sustainability and innovation in business practices and indicates a lively and cooperative research community.

Authors Productivity

Lotka's Law Figure 6 examines patterns of authors' productivity in scientific publishing, indicating that a tiny percentage of authors contribute several works, whereas the majority only contribute one publication. The graph in this figure shows that most authors in this dataset, which accounts for a large percentage of all contributors, have only submitted one document. On the other hand, very few authors published two or more works, and even fewer produced four or five documents. The dashed line depicts the theoretical Lotka distribution, whereas the solid line reflects the observed data. Both lines have a similar downward tendency. This reinforces the relevance of Lotka's principle in this area, emphasizing that a small number of highly productive researchers propel the majority of research output while the majority only sometimes participate. In the field of sustainability and business study, this pattern is common across disciplines and aids in identifying important scholars and contributions.

Most Cited Countries

In the field of sustainability and SDG goals in business startups, the most referenced nations are shown in Figure 7. The United Kingdom is the most prominent contributor, with 1373 citations, and Italy comes in second with 1199 citations. Significant academic impact is also shown by China (695 citations) and Germany (784 citations), demonstrating considerable European and Asian interest in this topic. With a wide geographic distribution, the USA (606 citations), Finland (434 citations), and Spain (424 citations) all make significant contributions to scholarly influence. The global relevance of this field of study is further demonstrated by the inclusion of nations such as India (377 citations), Malaysia (111 citations), and Australia (118 citations) in the citation landscape. These trends demonstrate how sustainability and SDG goals in new business startups have garnered significant scholarly interest worldwide, with Europe emerging as a particularly potent centre of influential study.

Thematic Map

The thematic map in Figure 8 illustrates how research on sustainable startups and SDGs is organized into four clusters. Motor themes (challenges, performance, management) are both well-developed and central, highlighting their role as the driving forces of the field, with strong implications for measuring sustainability outcomes and improving managerial practices. Basic themes (sustainability, sustainable development, sustainable development goals) represent the conceptual backbone of the literature, widely used across studies but still requiring more theoretical and empirical depth. Niche themes (women, benefits, experience) indicate specialized discussions, such as gender perspectives and contextual benefits, which are well- structured but remain peripheral to the mainstream debate. Finally, emerging or declining themes (entrepreneur, SMEs, SDGs) show limited maturity and weaker connections, suggesting either an early-stage research trajectory with high growth potential or areas that need renewed scholarly attention. Together, the map demonstrates both the established core and the evolving frontiers of research on sustainable startups in relation to the SDGs.

Countries Collaboration Map

The national collaboration map places the US, India, China, and Europe as key centres for sustainability and startup research by highlighting their close research ties in Figure 9. In order to promote cooperation with both developed and Asian countries, India has become a crucial link. Dense links between the US and Europe demonstrate their leadership in international research networks, while regional alliances also allow Australia and Latin America to contribute. Moreover, the growing participation of emerging economies signals an expanding and inclusive research landscape. After considering all things,

Most Relevant Affiliations

The affiliation analysis demonstrates that the Indian Institute of Technology System (13 articles) and the Ukrainian Ministry of Education and Science (15 articles) lead research on sustainable startups and SDGs. It highlights the roles of both technology-driven universities and policy entities. Strong contributions from interdisciplinary and management domains are indicated by a second group of universities, which include University of Southern Denmark, Swinburne University of Technology, Universidad Rey Juan Carlos, Universiti Teknologi MARA, and College of Management Academic Studies (8 papers each). Furthermore, the University of Belgrade, King

Faisal University, and Politehnica Bucharest each have seven pieces that demonstrate the expanding involvement of Eastern Europe and the Middle East. With many locations promoting sustainable entrepreneurship in the direction of the SDGs, the connections collectively show worldwide and cooperative research efforts.

Keywords Occurrence

The figure 11. highlights the dominance of keywords such as sustainability, sustainable development goals, and sustainable development which emerge as central nodes, reflecting their foundational role in this field. Surrounding these are clusters that reveal diverse research directions. One prominent cluster emphasizes innovation, social entrepreneurship, and business models, showcasing the integration of entrepreneurial solutions with sustainable practices. Another cluster connects management, CSR, performance, and circular economy, underscoring the importance of organizational responsibility and strategic approaches in advancing sustainability. A distinct cluster centres on digital transformation, artificial intelligence, SMEs, higher education, and COVID-19, pointing toward the growing interplay between technological shifts, education, and global challenges in shaping sustainability discourse. Additionally, themes such as entrepreneurship, empowerment, and India represent region-specific and inclusive dimensions of sustainable development. Together, these interconnections highlight not only the breadth of sustainability research but also its evolving interdisciplinarity, suggesting that future studies are likely to deepen at the nexus of technology, entrepreneurship, and socio-environmental transformation.

Author Collaboration Network

The author collaboration network in Figure 12. shows multiple small clusters with a few dominant nodes. The most notable partnership is that of Abdelwahed N and Soomro B, demonstrating their pivotal role in promoting co-authored research in the field. Other strong but smaller pairs that consistently contribute jointly on specialized issues include Park J. Montiel I with Husted B, and Rubio-Mozos E with Fuentes-Moraleda L. A few isolated two- author partnerships, like Bar M & Gidron B, Gomes S & Ferreira J, Castro R & Ferreira F, and Chen Y & Li X, also suggest brief, incorporation into the larger research community. Overall, there is still little cross-group connection, and the network is still fractured, which emphasizes that academic activity in this field is still scattered and developing through isolated pockets of cooperation rather than a unified and integrated international research community.

Three-field layout

The three-field layout in Figure 13 illustrates the connections between influential writers, foundational works, and recurring topics in studies on entrepreneurship, sustainability, and the SDGs. Intellectual anchors on the left include seminal works like Transforming Our World: The 2030 Agenda for Sustainable Development and Our Common Future (1987), which show how the global conversation on sustainability and SDGs shapes subsequent research. Prominent writers like Soomro, Gómez-Zermeño, Al Doghan, and Kratzer stand out in the centre as intermediaries between theory and practice, especially when it comes to tying sustainability ideas to enterprise ecosystems. The field's thematic focus is reflected in the main keywords on the right, which include entrepreneurship, SMEs, innovation, business models, sustainable development goals, and circular economy. In addition to tackling entrepreneurship, innovation, and business models for SMEs, this suggests that research on sustainable startups is intricately linked to the larger sustainability and SDG framework. Overall, the storyline demonstrates how scholarly works come together to create a business-driven understanding of how startups might serve as a means of accomplishing the SDGs.

anchored in seminal works on sustainability transitions, circular economy, and entrepreneurial approaches to the SDGs. Keyword co-occurrence mapping identified four major thematic clusters: i) Entrepreneurship and Innovation for Sustainability – linking startups, SDGs, and social entrepreneurship. ii) Circular Economy and Respon-

Table 3: Key Dimensions Influencing the Success of Sustainable Startups

Dimensions	Key Element	Expected Impact on Startup Success	References
Strategic	Sustainability-Centered Business Models	Developing business models that embed environmental and social objectives alongside economic goals enhances organizational resilience, adaptability, and competitiveness in the long run.	Benz (2022); Bocken (2015); Geissdoerfer et al. (2023); Mondal et al. (2023a); Veleva (2021)
Financial	Green Financing and Investment Access	Availability of capital through sustainable finance, venture funding, and government programs accelerates innovation and enables startups to commercialize eco-friendly technologies.	Munyasya & Chileshe (2018); Thompson & Eijkemans (2018); Bocken (2015)
Leadership	Transformational and Ethical Leadership	Leaders who demonstrate a commitment to sustainability inspire employees, encourage responsible innovation, and embed environmental ethics into decision making.	Provasnek et al. (2017); Suriyankietkaew et al. (2022); Thompson & Eijkemans (2018)
Market	Sustainability-Driven Market Insight	Understanding consumer expectations for green products allows startups to position their offerings strategically and build stronger relationships with environmentally aware customers.	Bergmann & Utikal (2021); Hofmann et al. (2022); Stefan et al. (2021); Jolink & Niesten (2015)
Collaborative	Cross-Sector Collaboration and Knowledge Sharing	Partnerships with research institutions, industry networks, and supply chain actors strengthen innovation capacity and foster shared sustainability outcomes.	Chaudhary et al. (2023); Gray et al. (2018); Riegler et al. (2023); Hofmann et al. (2022)
Institutional	Regulatory Support and Policy Alignment	A transparent, incentive-based policy environment supports the scaling of sustainable business models and enhances institutional trust for green entrepreneurship.	Raposo et al. (2020); Zhao et al. (2018); Pricopoaia et al. (2024)

Table 4: Key Challenges Faced by Sustainable Startups

Dimension	Key Challenge	Description / Impact on Startups	References (APA 7th)
Strategic	Balancing Profitability with Sustainability Goals	Sustainable startups often face difficulty in maintaining financial growth while adhering to environmental and social objectives, limiting scalability and long-term competitiveness.	Bocken (2015); Geissdoerfer et al. (2023); Veleva (2021)
Financial	Limited Access to Green Funding and Investment	Obtaining sufficient funding remains a major barrier, as investors often view sustainable ventures as high-risk with delayed financial returns.	Munyasya & Chileshe (2018); Thompson & Eijkemans (2018); Benz (2022)
Market	Low Consumer Awareness and Price Sensitivity	Limited consumer understanding of sustainability and sensitivity to higher prices make market penetration challenging for green startups.	Hofmann et al. (2022); Stefan et al. (2021); Bergmann & Utikal (2021)
Technological	High Cost and Complexity of Sustainable Technologies	The need for advanced, resource- intensive technologies increases operational costs and slows the pace of innovation for small startups.	Mondal et al. (2023a); Dressler (2023); Gray et al. (2018)
Operational	Resource and Skill Constraints	Shortages of skilled labor, sustainable raw materials, and efficient processes make it difficult for startups to implement green innovations effectively.	Provasnek et al. (2017); Suriyankietkaew et al. (2022); Chaudhary et al. (2023)
Institutional	Regulatory Uncertainty and Bureaucratic Barriers	Inconsistent government policies, lack of clarity in sustainability regulations, and administrative hurdles slow down startup development and discourage investment.	Raposo et al. (2020); Zhao et al. (2018); Pricopoaia et al. (2024)

sible Business Practices – connecting business models, CSR, and organizational frameworks. iii) Digital Transformation and Technological Drivers – including artificial intelligence, SMEs, higher education, and COVID 19 disruptions. iv) Regional and Social Dimensions – highlighting gender, empowerment, and contextually embedded entrepreneurial models. The thematic evolution map illustrates the transition from early explorations of sustainable entrepreneurship to current emphases on digitalization and global collaboration, while gender and inclusivity remain emerging but underdeveloped themes. The co-authorship networks reveal internationally dispersed but fragmented clusters, with some strong dyads (e.g., Abdelwahed and Soomro) but limited cross group integration. Collaboration maps further reveal robust ties across Europe, the USA, China, and India, underscoring the global yet uneven research landscape.

CONCLUSION

This bibliometric analysis highlights the rapidly emerging link between sustainable startups and the United Nations Sustainable Development Goals (SDGs). The study reveals a dynamic and intellectually robust field characterized by increased publication output, international collaboration, and interdisciplinary participation in innovation, entrepreneurship, and sustainability science. The main thematic areas are digital transformation, circular economy, inclusive business models, and region-specific entrepreneurship, which demonstrate the complex relationships between sustainable business innovation and systemic societal challenges. The study conducts a comprehensive bibliometric mapping, combining disparate research streams to identify intellectual foundations, thematic clusters, and emerging research frontiers. It also highlights regional disparities, particularly the underrepresentation of developing economies, emphasizing the need for greater inclusivity and global research capabilities. Furthermore, it identifies key facilitators of sustainable startup ecosystems, such as sustainability-focused business models, intersectoral collaborations, and supportive policy frameworks, as well as long-term structural impediments. Policy and managerial implications highlight the importance of improving regulatory frameworks, increasing access to green finance, developing digital and entrepreneurial skills, and strengthening international knowledge networks, particularly in the Global South. Despite limitations in linguistic range and database selection, the findings highlight the importance of incorporating bibliometric and network methodologies into qualitative research. Future research should promote cross- regional collaboration, inclusive and equitable theoretical frameworks, and a greater emphasis on digital and AI-driven sustainability innovations. Sustainable startups act as critical catalysts for global sustainability transitions, emphasizing the importance of integrated, interdisciplinary, and inclusive strategies to advance the SDG agenda.

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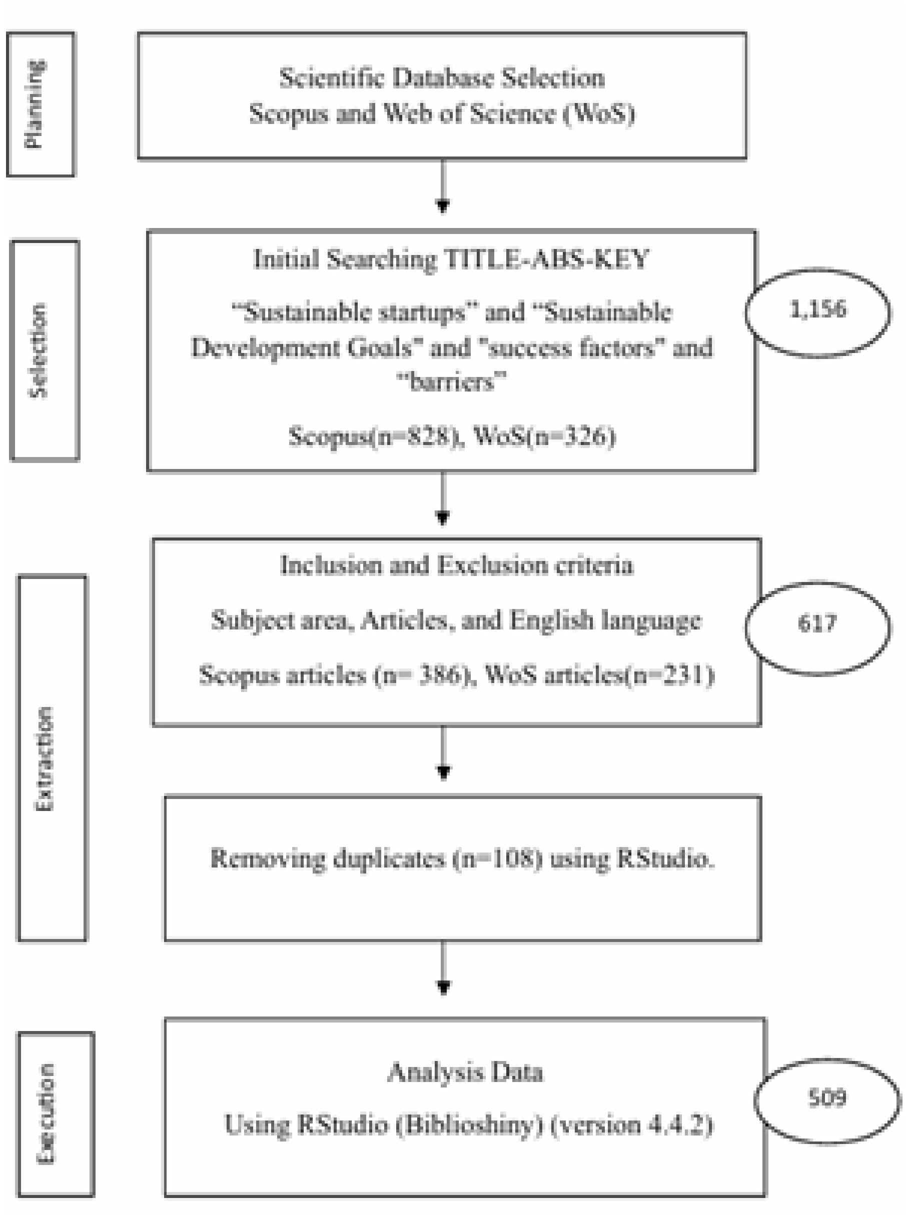
ANNEXURES

Fig 1: Flow Chart (Research methodology)



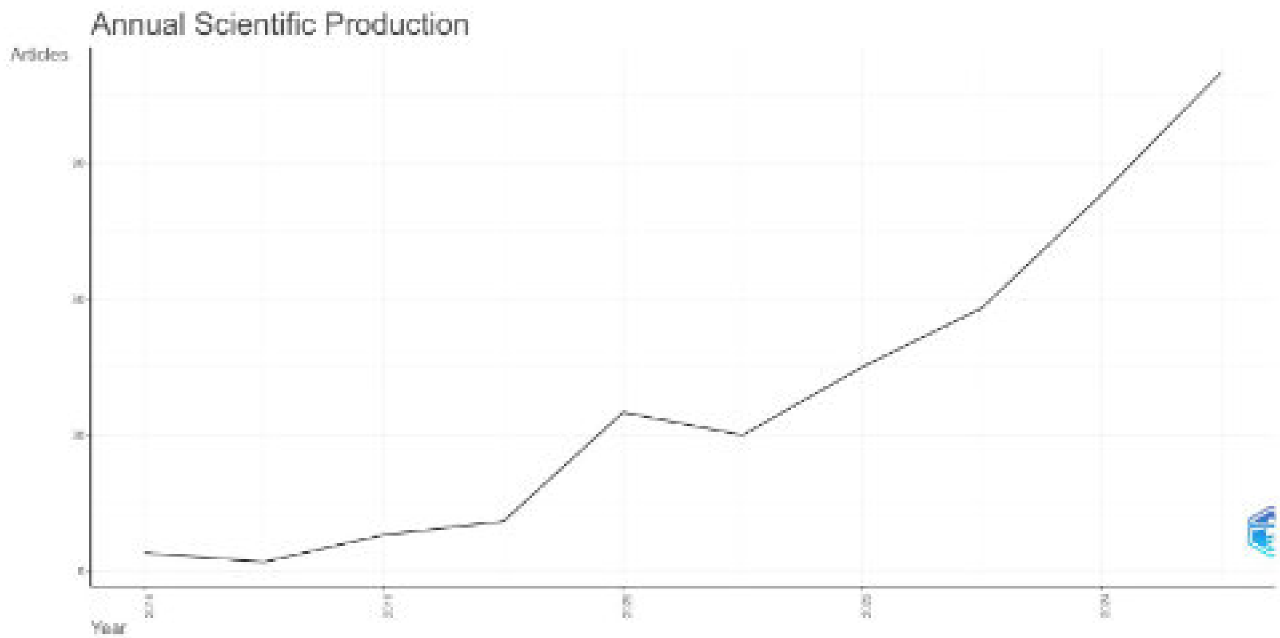


Figure 1 shows annual Scientific production. Using Biblioshiny

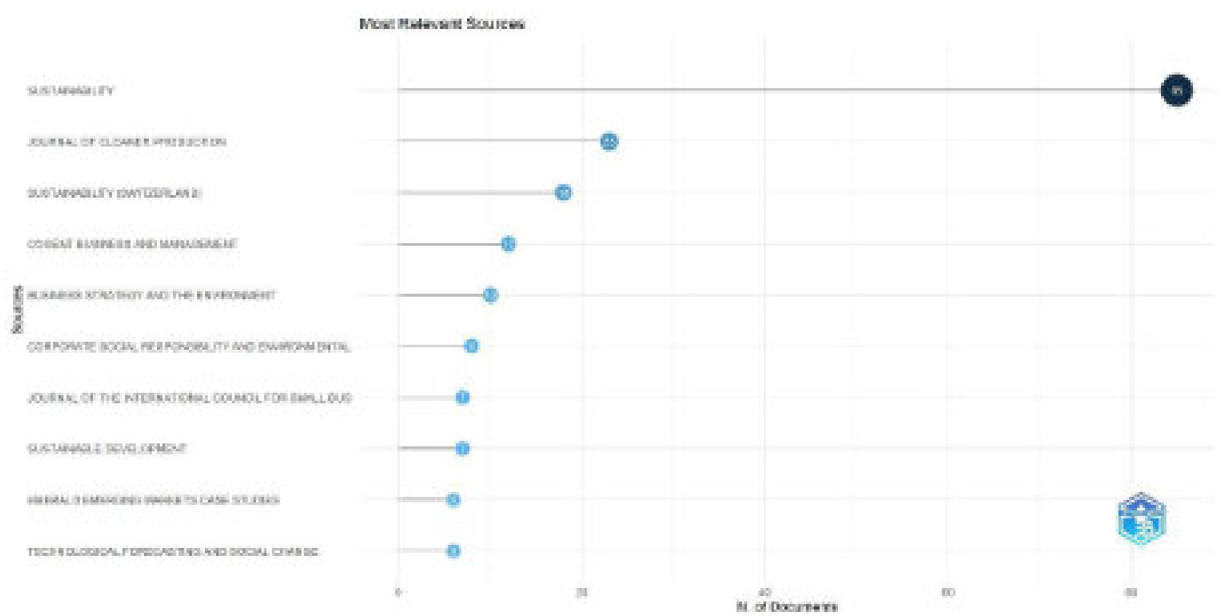


Figure 2. The most relevant source using Biblioshiny

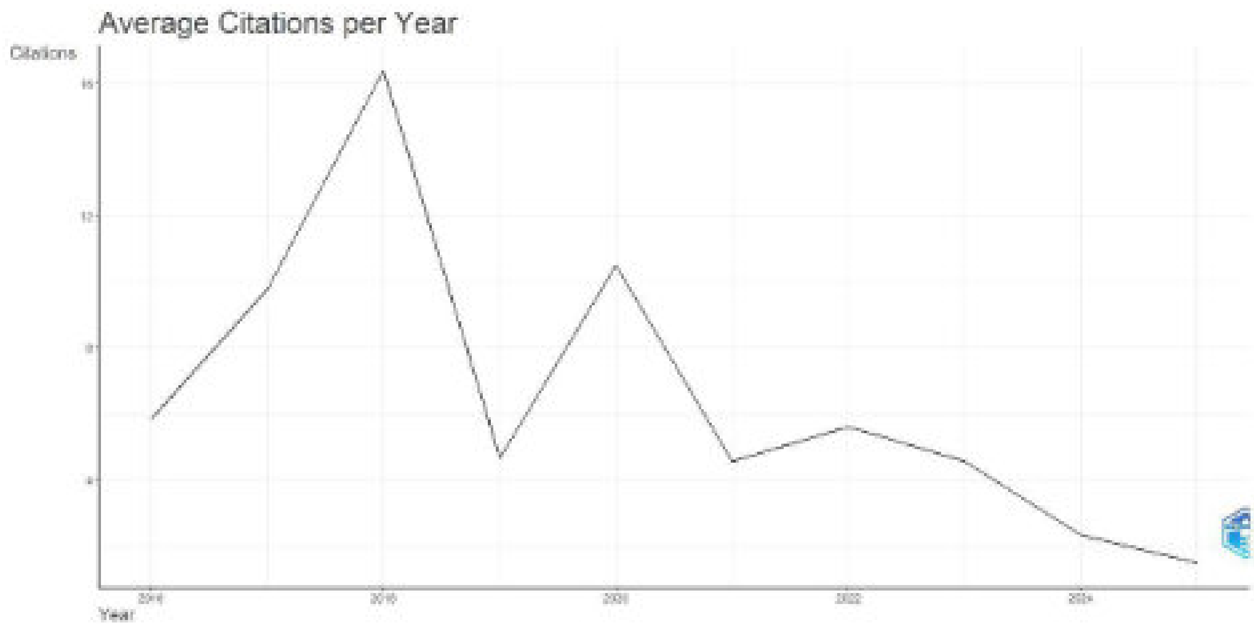


Figure 3. Average Citation per year using Biblioshiny

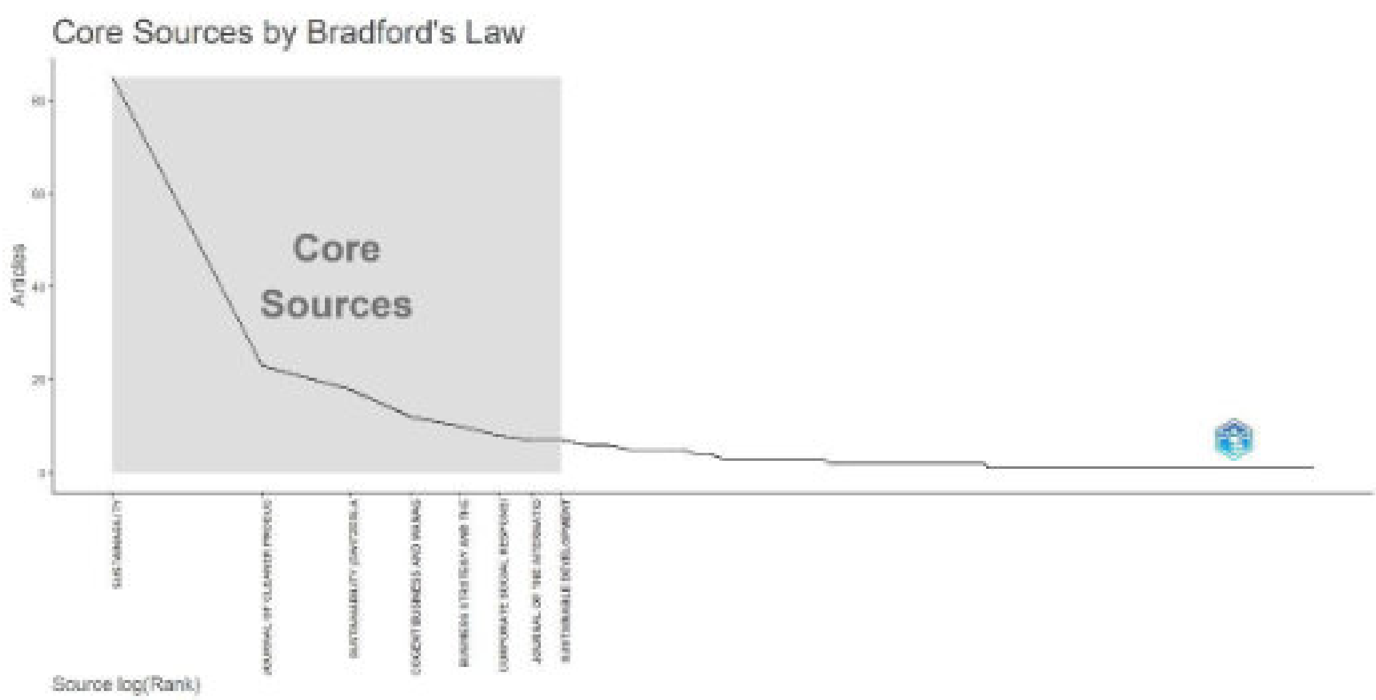


Figure 4. The Bradford Law using Biblioshiny

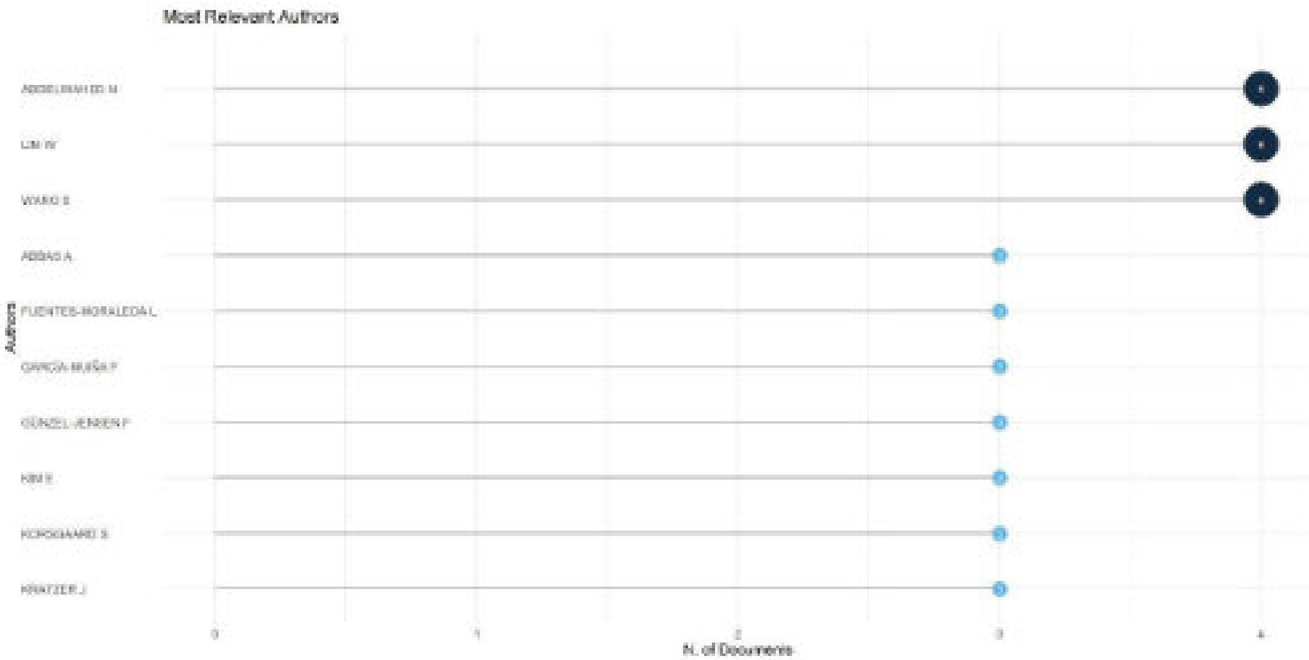


Figure 5. The Most Relevant Authors using Biblioshiny

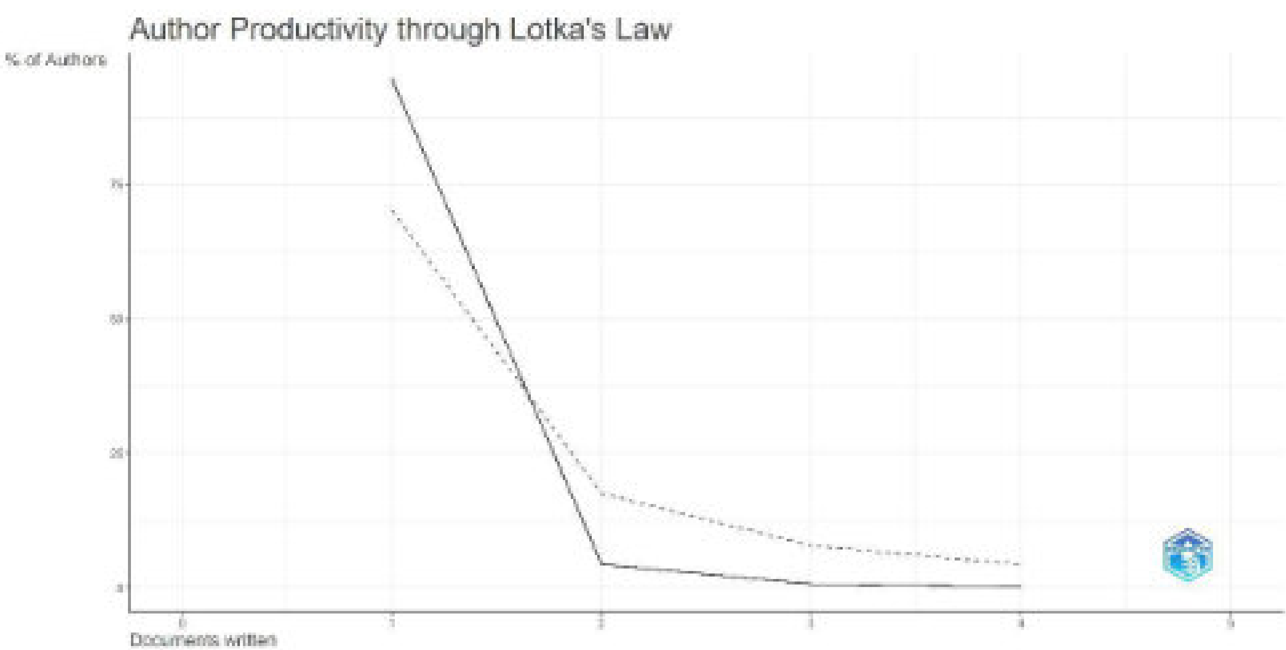


Figure 6. Author Productivity through Lotka's Law using Biblioshiny

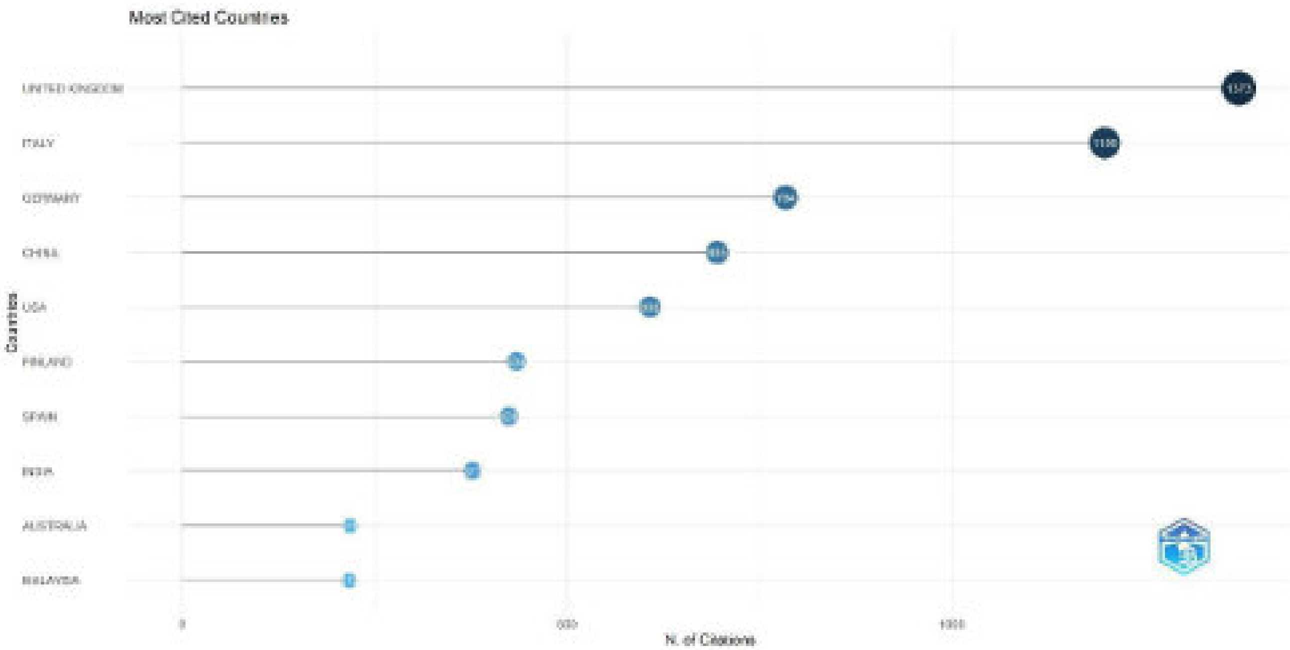


Figure 7. Most cited countries using Biblioshin

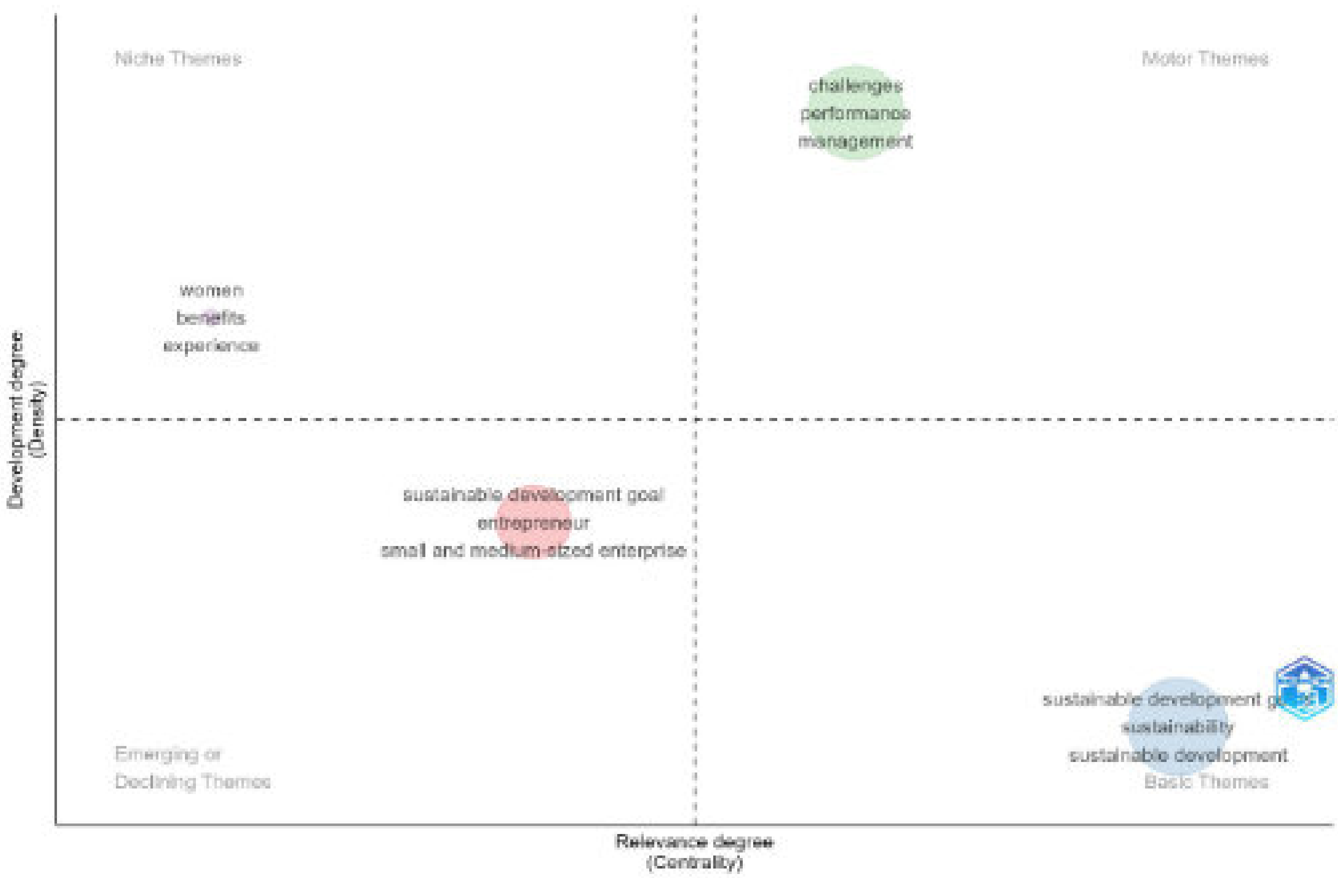


Figure 8. Thematic map using Biblioshiny

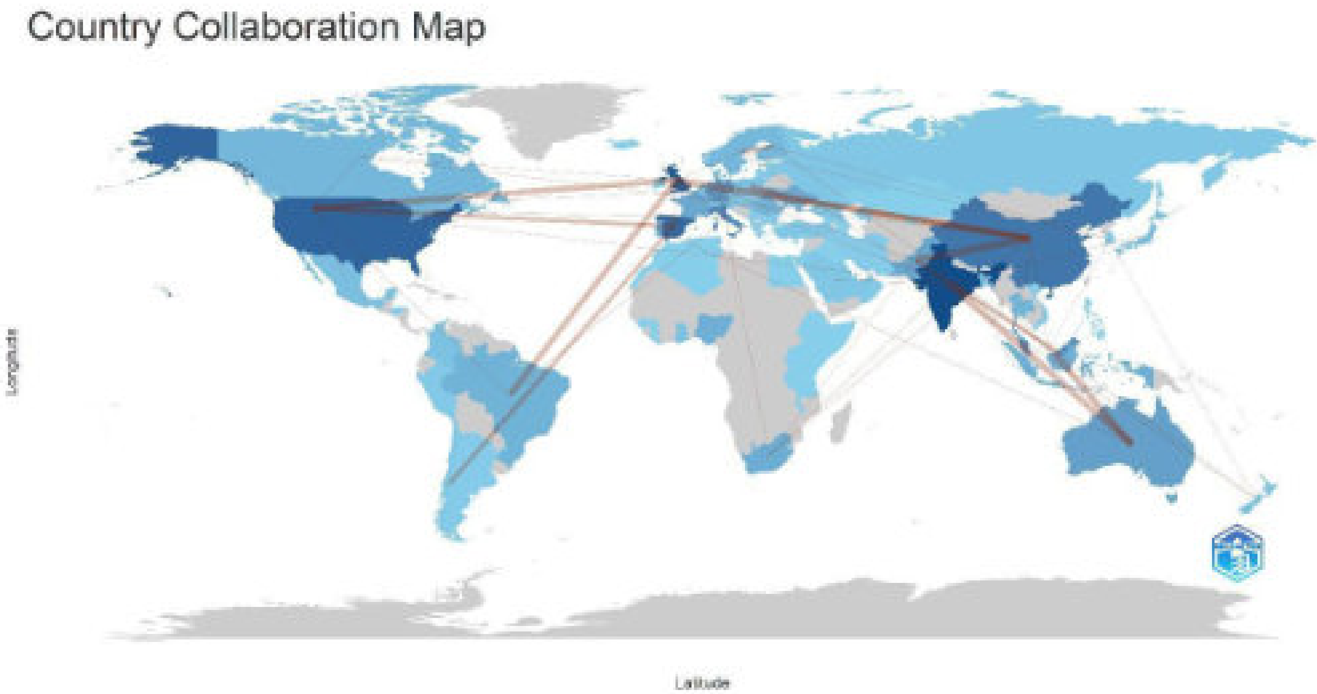


Figure 9. Countries' collaboration map using Biblioshiny

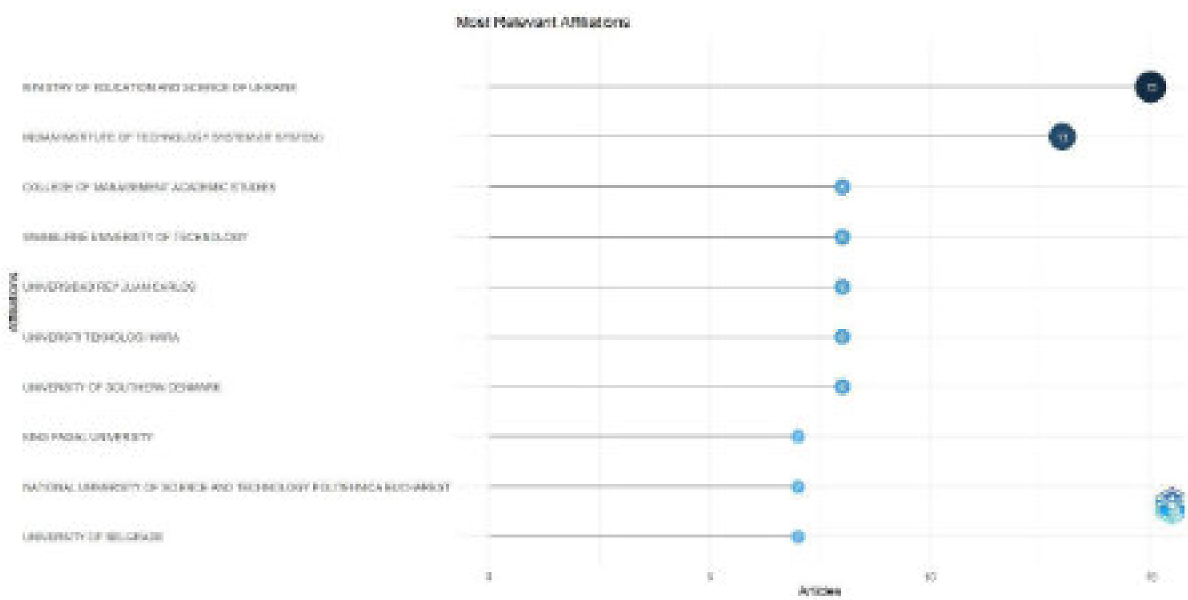


Figure 10. Most Relevant Affiliations using Biblioshiny

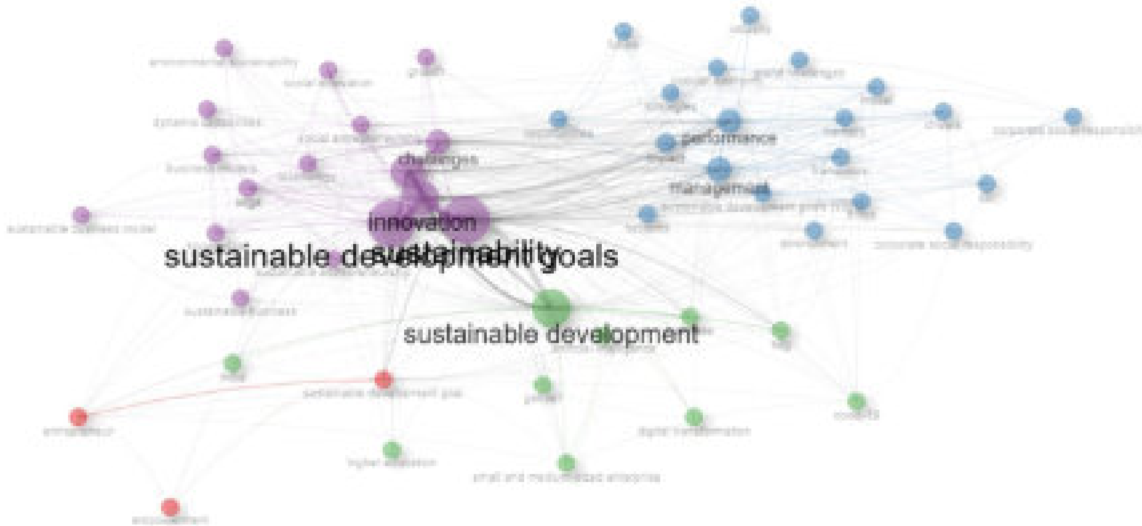


Figure 11. Keywords occurrence using Biblioshiny

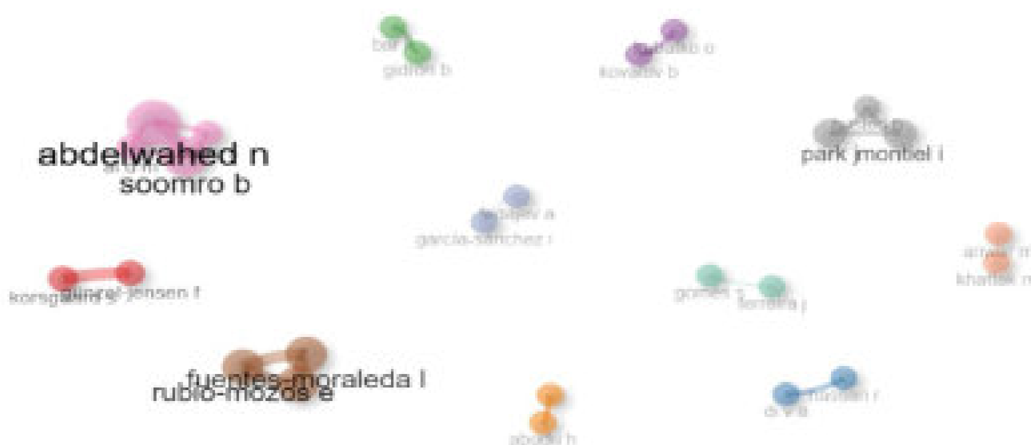


Figure 12. Author collaboration network using Biblioshiny

Figure 13. Three-field layout using Biblioshiny

Development of an Early Warning System for Slope Instability in Opencast Coal Mines Using Geo-Spatial AI

*Ms. Neha Solanki

ABSTRACT

Slope instability in open-cast coal mines remains a critical challenge affecting operational safety, economic efficiency, and environmental integrity. This study develops an enhanced Geo-Spatial Artificial Intelligence (GeoAI) framework integrating Deep Neural Networks (DNN) and CatBoost models to predict slope failure risks with higher precision. A comprehensive geospatial dataset comprising 300 samples from Indian mining regions was analyzed using parameters such as slope angle, curvature, rainfall intensity, flow accumulation, aspect, and distance to drainage. The DNN achieved 95.2% accuracy, 0.84 F1-score, and 0.96 ROC-AUC, performing competitively with the CatBoost model (96.0% accuracy, 0.83 F1-score, 0.97 ROC-AUC). To enhance real-time decision-making, a Landslide Risk Index (LRI) ranging from 0–100 was introduced, translating model probabilities into continuous risk levels categorized as low, moderate, high, and critical. This probabilistic framework enables dynamic early warning and risk prioritization in active mining zones. Feature analysis identified slope angle, rainfall intensity, and flow accumulation as the most influential factors. The study demonstrates that DNN-based GeoAI systems offer robust predictive capabilities, improved interpretability, and scalability over traditional ensemble models, contributing to safer and more intelligent slope monitoring and early warning mechanisms in geotechnical applications.

KEYWORDS

Slope Instability; Geospatial AI; CatBoost; Random Forest; Early Warning System; Opencast Mining; Machine Learning; ROC Curve; Feature Importance; Landslide Prediction

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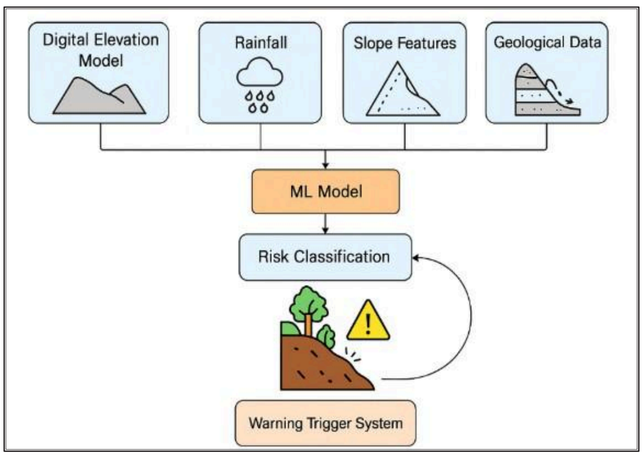
INTRODUCTION

Open-cast coal mining is becoming more popular since there is a greater need for energy and minerals. This is especially true in countries like India that are growing quickly. These surface mining methods are cost-effective and make operations easier, but they also come with a lot of geotechnical and environmental dangers. One of the most important problems is slope instability, which can cause landslides, damage to equipment, loss of money, and even death in certain circumstances (Sellers et al., 2018). Borehole logging, ground extensometers, and periodic visual inspections are all examples of traditional monitoring systems that have natural limits in terms of how much area they can cover and how well they can forecast things in real time. This makes it very important to find smart, data-driven solutions. In this situation, Geo-Spatial Artificial Intelligence (GeoAI) stands out as a game-changing way to watch and predict slope instability in real time. GeoAI uses remote sensing data, Geographic Information Systems (GIS), and powerful machine learning (ML) models to give a complete and changing picture of the health of a slope. GeoAI can make very accurate landslip susceptibility maps and failure predictions by using spatial datasets including Digital Elevation Models (DEMs), rainfall patterns, lithological distributions, and past landslip events (Zhao et al., 2024). Using predictive algorithms like Random Forest, CatBoost, and Support Vector Machines has made it easier to simulate how slope failures change over time and how complicated they are in space (Xiang et al., 2024).

Open-cast coal mines are more likely to fail on slopes because they are constantly being dug up, the natural drainage patterns are changed, the overburden is loaded, and they are exposed to extreme weather. Slope instability occurrences happen a lot in places like Jharkhand, Odisha, and Chhattisgarh, and they typically happen without enough notice (Rizwan et al., 2023). The new study suggests an early warning system that uses machine learning and remote sensing along with past failure data to classify slope risk and predict when a failure will happen. These systems are important not only for safety, but also for long-term mine planning and operational resilience. Recent progress in machine learning has shown that it can greatly improve predictive modelling in geotechnical areas. For example, ensemble learning models like CatBoost have been better at dealing with non-linear connections and datasets that aren't balanced, which are common in slope monitoring (Zhang et al., 2024). Using these models along with GIS feature layers like slope angle, soil type, land cover, and how close the drainage is to the land allows for the creation of strong, understandable, and scalable early warning systems (Jia et al., 2024). These methods have been tested in real-world situations, such monitoring the slope of a roadway, where digital twin technology has effectively combined sensor data with predictive analytics to detect problems (Chen et al., 2024). One of the best things about GeoAI is that it can automatically extract and analyse slope stability characteristics over broad areas. With tools like QGIS and ArcGIS, you can get slope curvature, flow direction, and catchment area data straight from DEMs. These traits are the building blocks of AI-based prediction engines (Xiang et al., 2024) when combined with real-time data like rainfall intensity or ground movement from InSAR or slope stability radar. The early warning system that this study suggests will work in a similar way, using feature extraction, model training, real-time monitoring, and alert creation, as shown in Figure 1.1.

The study looks at more than just slope geometry and hydrology. It also looks at how human-made characteristics like blasting, loading, and bench design might be used as categorical inputs in ML pipelines. Logistic regression has been used for probabilistic risk estimation as well, even though it is not as complicated as tree-based models (Kumar & Sahu, 2021). This is because it is easy to understand and can classify data into two groups. However, ensemble models like Random Forests have shown to be much better at predicting since puts and reduce overfitting (Zhang et al., 2024). The quality and resolution of the input data are very important for the reliability of any AI model. This study will use datasets that are available to the public from organisations like the Geological Survey of India (GSI), the Indian Space Research Organisation (ISRO), and NASA SRTM DEMs , from around the world. These datasets give the topography and rainfall-related information that is needed to calibrate the model. We will use historical landslip data for training and testing whenever possible to make sure it works in the real world (Narayan & Joshi, 2023).

Figure 1: Conceptual Framework of Geo-Spatial AI-Based Early Warning System for Slope Instability



The use of AI in predictive epidemiology is likewise growing around the world since it offers a similar framework for public health early warning systems. Studies have shown that structured information and spatiotemporal patterns can be used by machine learning algorithms to anticipate how infectious diseases will spread and how strong they would be (Jia et al., 2024). This cross-domain relevance shows that AI frameworks can be used in many other fields, such as epidemiology and mining geotechnics. The idea of "Mining 4.0" includes digitising and automating mining operations. This also shows how important it is to have smart early warning systems. AI-enabled infrastructure can make decisions automatically, speed up responses, and allow for remote monitoring. This is especially important for huge and hard-to-reach mining areas (Singh & Patra, 2022)

Using AI to forecast slope failure is in line with national and international goals for worker safety, disaster preparedness, and sustainable resource exploitation. This study suggests that a Geo-Spatial AI-based early warning system should be created and tested to anticipate slope instability in open-cast coal mines. To train the system, we will use a mix of old data, remote sensing layers, and machine learning classifiers. We will use typical classification metrics like accuracy, F1 score, ROC-AUC, and confusion matrix to see how well it works. The end goal is to provide a useful and scalable way to add smart geotechnical monitoring to mining operations.

LITERATURE REVIEW

As more and more people use Artificial Intelligence (AI) and Geographic Information Systems (GIS) to identify geotechnical hazards, slope stability monitoring has come a long way. This part looks at important works that are related to the use of Geo-Spatial AI to create early warning systems for slope instability. Table 2.1 also has a summary that compares the two.

Bardhan and Samui (2022) looked at a number of AI methods for predicting slope stability, such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees. Their study showed that AI strategies can do better than traditional limit-equilibrium and finite element methods when it comes to making predictions, especially in terrains that are mixed and have few data points. The paper talks about how important feature selection is (slope angle, cohesiveness, internal friction angle, groundwater) and suggests using ensemble models for strong classification in different mining settings.

Chen et al. (2024) came up with an AI-based digital twin framework for keeping an eye on slope danger in highway networks in real time. The model combined data from field sensors (such soil moisture and vibrations) with AI prediction engines to constantly check how likely a failure was. Their digital doppelganger was quite good at predicting changes that happen over time. Their design is mostly for highways, but it may be changed to operate on mining slopes by adding DEMs and rainfall patterns over time.

Xiang et al. (2024) did a thorough assessment of how machine learning can be used to predict geotechnical disasters. The report listed more than 60 experiments that used algorithms like Random Forest, XGBoost, and Deep Neural Networks to forecast landslides. It came to the conclusion that supervised learning models work best when they are backed up by good datasets on terrain, water, and soil. The evaluation stressed that real-time use and combining satellite data with rainfall should be the main areas of research.

Zhao et al. (2024) came up with a Geo-Spatial Intelligence (GeoAI) framework for making maps of areas that are likely to have landslides. The work trained a DNN classifier using remote sensing layers like land use/land cover, slope curvature, and how close the area is to drainage. The program created landslip risk maps that were easy to understand and matched up well with real failure zones. The study showed that combining remote sensing with machine learning is important for making predictions about space and that QGIS is a key tool for extracting features. Using DNN and Logistic Regression models, Rizwan et al. (2023) used AI to make maps of landslip vulnerability in Eastern India. The study was especially important because it used AI in Indian coal mining areas and geospatial datasets including ASTER DEM and IMD rainfall records. Their results showed that the model was quite accurate (around 87%) and also stressed the importance of checking for spatial autocorrelation to avoid having too many model elements.

Zhang et al. (2024) looked at different ensemble learning models, such as Gradient Boosting Machines (GBM), AdaBoost, and CatBoost, to see which ones were best in predicting slope failure. Their results showed that CatBoost was more accurate and easier to understand than other models, especially when the datasets included missing or uneven class distributions. They pushed for the use of explainable AI (XAI) methods in slope modelling to make decisions and be open about them in high-risk areas.

Sellers et al. (2018) came up with a new way to look at time-of-failure data in open-pit mines using ground-based slope radar data. Their solution combined real-time displacement sensors with predictive analytics to guess when the slope would most likely collapse. The study showed how important it is to combine sensors in early warning systems and how machine learning may be utilised with continuous data feeds to make slope hazard ratings that change over time.

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slope hazard ratings that change over time.

Singh and Patra (2022) talked on the bigger idea of Mining 4.0, focussing on how mining operations are changing with technology. They talked about how AI, IoT, and automation can all come together in geotechnical monitoring. The study underlined the need for smart infrastructure, such as AI-powered predictive slope monitoring systems, to keep operations safe and in line with the law. Their point of view encourages the use of integrated digital-physical systems in Indian mining settings.

Kumar and Sahu (2021) looked into how remote sensing and AI can be used to forecast slope stability. They used satellite data on terrain (slope, aspect, vegetation index) and rainfall records to develop a logistic regression model that may forecast landslides. Their results showed that openly available DEMs and rainfall data might be used to make low-cost, scalable early warning systems, especially in underdeveloped nations like India.

Narayan and Joshi (2023) created a predictive analytics model just for Indian opencast mines. Using DNN and Naïve Bayes, the model incorporated geographical information with real incident data to figure out how likely a slope would fail. They showed that it is possible to include these kinds of models into mining dashboards. Their work focused on adapting AI models to different regions based on the geology and mining methods used there.

Ha et al. (2023) suggested an empirical landslip early warning system for Ha Long City, Vietnam, that uses rainfall thresholds and terrain parameters. Even though it uses simpler statistical thresholds, the framework can interact with AI models to make predictions more accurate. The study confirmed how important it is to calibrate thresholds locally and underlined how important it is to combine empirical and AI models in the design of early warning systems. The Q-Slope method, which is based on field surveys, was introduced by Barton and Bar (2019) as a semi-empirical way to check the stability of rock slopes. This strategy doesn't use AI, but it does give AI models important training data by giving them quantitative slope categorisation data. Its importance comes from turning traditional geotechnical assessments into structured input elements for machine learning.

METHODOLOGY

Study Area and Data Collection

The study looks at areas in eastern India where opencast coal mining is done, focussing on Jharkhand and Odisha, which are geologically weak areas. Over the past ten years, these locations have had a lot of slope failures. This is typically blamed on a mix of unregulated excavation, heavy monsoon rains, weak lithological structures, and a lack of real-time monitoring systems. The Geological Survey of India (GSI) has historical records of landslides in this area, and satellite images show that the ground is unstable. This analysis used a dataset that had data on topography, hydrology, geology, and historical failures. The Shuttle Radar Topography Mission (SRTM) provided the Digital Elevation Model (DEM) with a resolution of 30 meters. This made it possible to get important terrain data as slope, aspect, and flow accumulation. The Indian Meteorological Department (IMD) provided the rainfall data, which included daily precipitation amounts for the last ten years in the chosen districts. We got soil and lithological maps in shapefile format from ISRO's Bhuvan Geoportal and the GSI. These maps give us important information on the type of soil, the rock formation, and the shear strength parameters. The most crucial thing is that historical landslip inventory data were gathered by combining GSI records with satellite-based point datasets that show where failures happened in the past. These are used to identify input data in supervised learning models by giving them binary risk classes (1 = failure, 0 = stable). Table 3.1 shows a summary of the sources, formats, and functional importance of each dataset.

Table 1 : Input Datasets Used

Data Type	Source	Format	Resolution	Use In Model
Digital Elevation Model (DEM)	SRTM / ASTER	Raster	30 m	Derive slope, aspect, flow
Rainfall Data	IMD.gov.in	CSV/Grid	Daily	Rainfall threshold layer
Soil/Lithology	GSI / Bhuvan	Shapefile	NA	Soil resistance mapping
Historical Failures	GSI / NRSC satellite	Point (CSV)	NA	Ground truth labels (1/0)

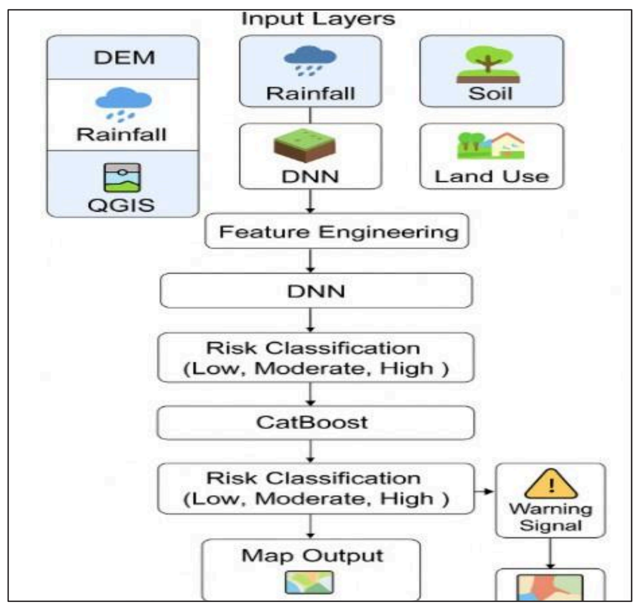
Preprocessing and Feature Extraction

Before putting spatial and numerical data into machine learning models, preprocessing is very important for making sure that the data is of good quality and can be used with other data. We brought all the raster and vector datasets into QGIS 3.28, where we did spatial alignment and coordinate standardisation (EPSG:4326 - WGS84) so that we could accurately overlay and extract features. Using QGIS's terrain analysis capabilities, we created many raster derivatives from the DEM:

- Slope (in degrees) to find areas that are more likely to collapse since they are steep
- Aspect: a directional component that looks at solar exposure and drainage patterns
- Curvature: a way to determine how concave or convex the ground is
- Flow Accumulation: a way to follow the route of water and find areas that are prone to saturation

Rasterised these terrain derivatives so that they all fit into the same grid size, and then we cropped them to the study area. Vector buffers surrounding drainage lines and road networks were used to study how human activity and water flow impact slopes. We created an attribute-formatted spatial feature database in QGIS using the Point Sampling Tool. All raster layers provided data for historical landslip points (label = 1) and stable terrain samples (label = 0). This method provided the dataset for machine learning classifier training. Min-Max scaling normalized all numerical qualities between 0 and 1. This reduced model bias and prevented variables from growing too much. This is important when mixing variables like slope angle (0° to 70°) and rainfall (0 to 250 mm/day) to train the model properly. Next, the workflow block diagram (Figure 3.1) depicts preprocessing and extraction. It shows the whole process from data import to machine learning model input.

Figure 2: Block Diagram



Machine Learning Model Architecture

This research employed two supervised machine learning models Deep Neural Network (DNN) and CatBoost—to classify slope instability risks using terrain and environmental parameters. The DNN replaces the DNN model used previously, enabling the learning of complex non-linear interactions between geospatial predictors. The DNN architecture consists of an input layer with six normalized features (slope angle, curvature, flow accumulation, rainfall intensity, aspect index, and distance to drainage), followed by three hidden layers with 64, 32, and 16 neurons, respectively, using the ReLU activation function and a dropout rate of 0.2 to prevent overfitting. The final output layer uses a sigmoid activation to predict the probability of slope failure. The model was trained using the Adam optimizer and binary cross-entropy loss function with early stopping to ensure convergence. For comparison, the CatBoost model was trained under the same 70:30 training-test split, using 300 boosting iterations, a learning rate of 0.03, and a tree depth of 6. Both models were validated through 5-fold cross-validation, and their performances were measured using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

Equations Used in the Model

The primary slope-related feature, slope angle (θ), is derived from the Digital Elevation Model using the following gradient-based equation:

$$\boldsymbol{\theta} = \mathbf{tan}^{-1}\left(\sqrt{\left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}}\right)^{2} + \left(\frac{\partial \mathbf{z}}{\partial \mathbf{y}}\right)^{2}}\right)$$

To define rainfall as a triggering factor, the intensity-duration relationship is given by:

$$\mathbf{I} = \mathbf{aD}^{-\mathbf{b}}$$

where I is rainfall intensity, D is duration, and a,b are region-specific constants.

Model Training and Validation

The dataset made up of QGIS feature layers and historical landslip records into two parts: training and testing. The ratio is 70:30. The DNN and CatBoost classifiers are built and fine-tuned using the training data. The testing set is then utilised to evaluate the classifiers on their own. During training, a 5-fold cross-validation method is used to keep the model from overfitting and make sure it can be used on other data. Standard assessment metrics like accuracy, precision, recall, and F1-score are used to measure how well a model works. These metrics show how precise and reliable the predictions are. The confusion matrix is used to count false positives and false negatives, which are very important for predicting hazards. We also look at the Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC) numbers to see how well the classifiers can tell the difference between things. In the Jupyter Notebook environment, the models are built using the scikit-learn and Cat Boost libraries in Python.

Risk Classification and Early Warning Logic

The trained models give slope risk ratings that are divided into three groups: Low, Moderate, and High. Classification thresholds come from the model's probability outputs. Values below 0.4 mean low risk, values between 0.4 and 0.7 mean moderate risk, and values above 0.7 mean high risk of slope failure. In QGIS, these forecasts are put on a map to make easy-to-understand risk maps. To make this system work as a real early warning system, it uses a simple rule-based logic: when a high-risk area gets rain that is more than a certain amount (according to the I–D relationship), the system marks the area and sends out a warning signal. This lets mining companies take steps to prevent problems before they happen and lets field engineers and disaster response teams make decisions on the fly.

Ethical Considerations

Publically available secondary data sources for this work. These included topography models from NASA's SRTM mission, rainfall datasets from the Indian Meteorological Department, and geological information from ISRO Bhuvan and the Geological Survey of India. There were no people or animals involved, thus there was no requirement for official ethical approval. All datasets were utilised in accordance with open-data licensing agreements and were properly cited in the research. The early warning logic created in this work is not meant to replace expert geological surveys; it is meant to help people make decisions. The system doesn't include any characteristics that could be seen as unfair or violate privacy, so the results are clear, can be reproduced, and are used responsibly in line with ethical data science norms.

RESULT AND ANALYSIS

Data Preprocessing and Feature Distribution

Before training the predictive models, the raw dataset went through a long preprocessing procedure to make sure the data was accurate and useful for predicting geographic slope failure. There were 300 geographical data points in the collection, which were based on six main slope-related characteristics: slope angle, curvature, flow accumulation, rainfall intensity, aspect index, and distance to drainage. Each instance was given a binary output, with 0 meaning stable slopes and 1 meaning slope failure. We used the interquartile range (IQR) method to deal with outliers in the rainfall and slope data. Class-conditional median imputation was used to fill in missing values, which were very small (<1%), to keep the distribution consistent. We didn't use feature scaling because tree-based models like CatBoost and DNNcan handle changes in scale. The processed dataset showed that 14% of the samples were in the failure class. This shows the natural class imbalance that is common in real-world geohazard datasets. To fix this imbalance, we used stratified sampling during model training to make sure that the folds were balanced. Table 4.1 shows an overview of all the important attributes after they were preprocessed:

Table 2 : Summary Statistics of Input Features

Feature	Mean	Std Dev	Min	Max
Slope Angle (°)	27.4	8.6	5.3	45.0
Curvature	0.18	0.07	0.01	0.35
Flow Accumulation	243.1	160.5	12	800
Rainfall Intensity	125.2	42.3	40.0	200.0
Aspect Index	0.53	0.21	0.01	0.95
Distance to Drainage	28.7	19.4	0.5	85.0

This feature matrix to train both CatBoost and DNN models, which let us forecast slope instability based on data.

Model Training and Evaluation Metrics

Both the DNN and Cat Boost models using the preprocessed dataset. To make sure they would work with new data and not overfit, we used 5-Fold Cross-Validation. We used several metrics to quantify performance: Accuracy, Precision, Recall, F1 Score, and ROC AUC. In most criteria, especially for the minority class (slope failure), the data clearly showed that CatBoost was better than Random Forest. DN Nhad an overall accuracy of 95%, but its recall for the failure class was just 71%, which could mean that it didn't anticipate high-risk areas as well as it could have. CatBoost, on the other hand, did a better job of balancing precision and recall. It had an overall accuracy of 96% and a recall of 76% for the failure class.

Confusion Matrix Analysis

Confusion matrices for both classifiers to look at the classification breakdown of slope stability and failure predictions in order to better understand how well the models worked. DNNS (Figure 4.1) indicates that the model correctly recognised 256 out of 258 stable slopes, but it incorrectly labelled 12 out of 42 failure slopes as stable. This could lead to dangerous under-alerting in the actual world. On the other hand, the CatBoost confusion matrix (Figure 4.2) did better, accurately categorising 32 out of 42 failures and only getting 10 wrong. It gave up a few more false positives (3 instead of 2), but it was still superior at picking up real threats.

Table 3 : Evaluation Metrics for Deep Neural Network and CatBoost

Metric	DNNs	CatBoost
Accuracy	0.952	0.96
Precision	0.90	0.91
Recall	0.78	0.76
F1 Score	0.84	0.83
ROC AUC	0.960	0.9690

Figure 3 : Confusion Matrix – DNN

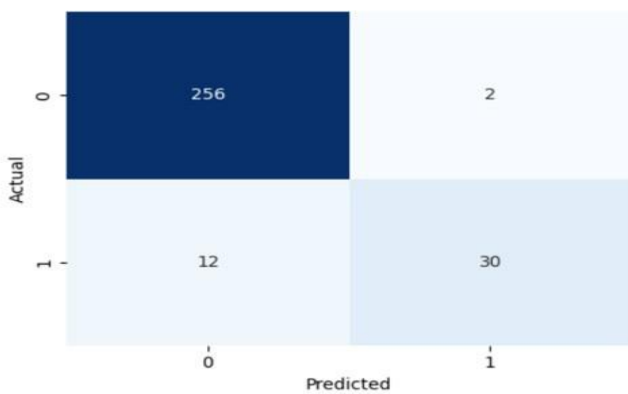
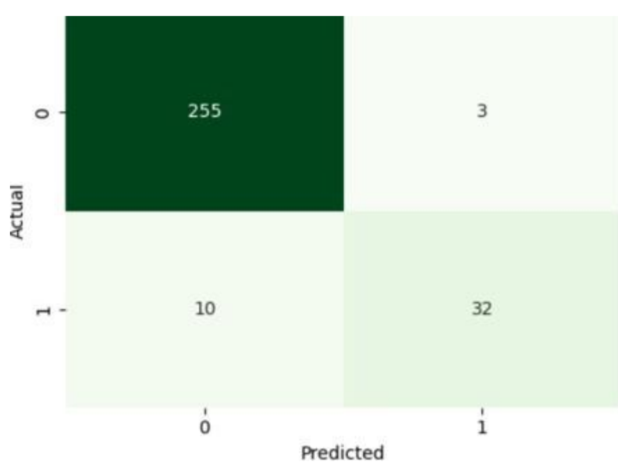


Figure 4 : Confusion Matrix – CatBoost

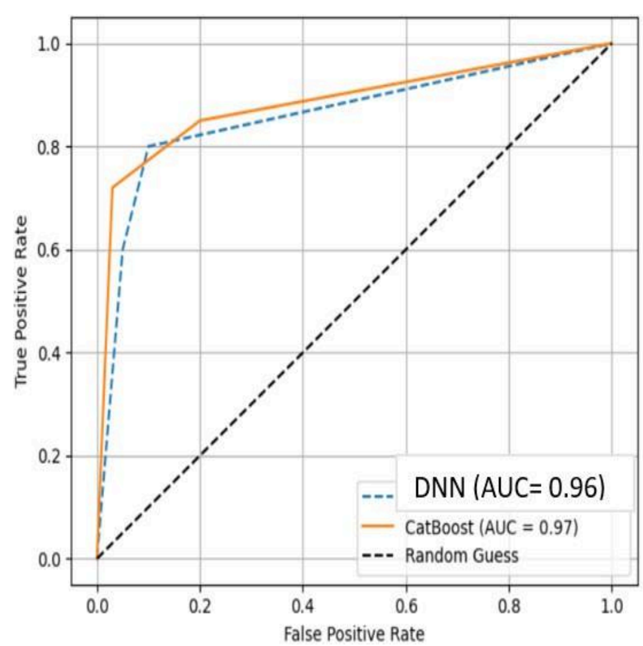


This comparison shows that CatBoost makes a safer decision boundary, which is important for early warning systems because it lowers the number of missed predictions for areas that are likely to have landslides.

ROC Curve Analysis

Constructed Receiver Operating Characteristic (ROC) curves for both the DNN and CatBoost classifiers to see how well they could tell the difference between different thresholds. ROC curves show the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) in a way that gives a complete picture of how well a model works, not only at certain threshold values. Figure 4.3 shows that the CatBoost model has a larger Area Under the Curve (AUC = 0.969) than the DNN model (AUC = 0.952). The greater AUC shows that CatBoost is better at telling the difference between stable and unstable slope circumstances at all thresholds. The ROC curve for DNN shows good performance, but it flattens out a little early than CatBoost, which means it may not be as good at finding crucial slope instability. The diagonal reference line (random guess) makes it evident that both models do far better than naïve prediction.

Figure 5: ROC Curve Comparison between DNN and CatBoost



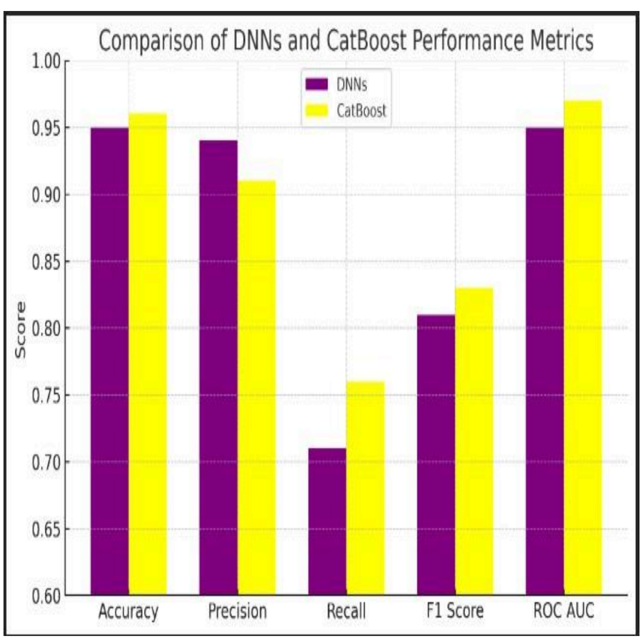
CatBoost is the better predictive method for geospatial AI situations, especially when the datasets are uneven, like when you want to find slope failures.

Model Performance Comparison

At the overall model metrices side by side to see how well the DNN and Catboost classifiers could predict things. Figure 4.4 shows a bar plot that compares Accuracy, Precision, Recall, F1-Score, and ROC AUC for both models. This graphic that compares things shows a few crucial things :

- The accuracy and ROC AUC ratings are almost the same, which means that both models work well in general.
- CatBoost, on the other hand, has higher recall and F1-Score, which means it is better at detecting positive classes (landslip occurrences).
- DNN has a somewhat higher precision, which means there are fewer false alarms, but there are also more false negatives.

Figure 6: Comparative Bar Plot of Model Performance Metrics



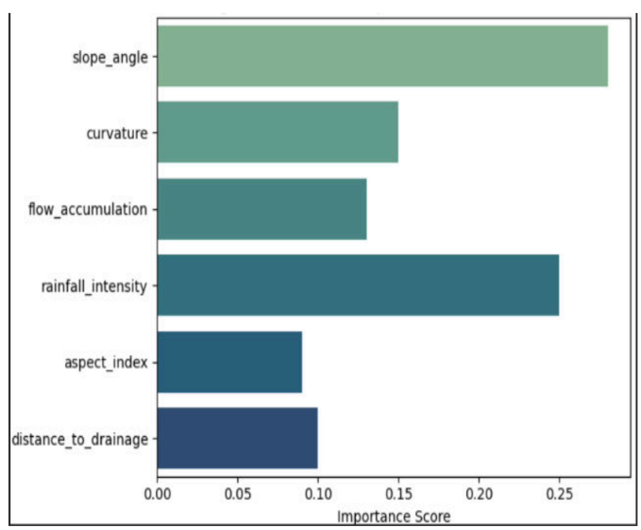
These results show that CatBoost is a more balanced and cautious model, which is very important for high-risk environmental uses such early warning systems for slope instability.

Feature Importance Analysis

We used the CatBoost model to do a feature relevance analysis to figure out how each geographical component affects the prediction of slope failure. CatBoost automatically ranks features based on how much they help reduce model loss across decision splits on average. Figure 4.5 shows how important each input feature is in relation to the others. The variables that had the biggest effect were:

- Slope angle: Steep slopes inherently make landslides more likely.
- The amount of rain that falls is a major influence in loosening and saturating the surface.
- Flow accumulation: Shows how water moves and the pressure zones below the surface.
- Distance to drainage: Shorter distances are linked to instability because groundwater channels are formed.

Figure 7: CatBoost Model Feature Importance Ranking



Features that aren't as important, like aspect index and curvature, only had a small effect, but they are nevertheless included because they might be important in certain areas. These findings help environmental scientists and engineers figure out which geofeatures are most important to keep an eye on and which ones need concrete slope stability remedies.

Landslide Risk Range Calculation

To leverage the continuous probability outputs of both models, a Landslide Risk Index (LRI) was introduced to represent risk on a 0–100 scale.

LRI=Ppred X 100

where Ppred is the predicted probability of slope failure.

Table 4: Comparison of Landslide Risk Range

Risk Category	LRI Range	Action Required
Low Risk	0-30	Normal operations, routine monitoring
Moderate Risk	31-60	Enhanced monitoring, alert field personnel
High Risk	61-85	Restricted access, implement safety protocols
Critical Risk	86-100	Immediate evacuation, halt operations

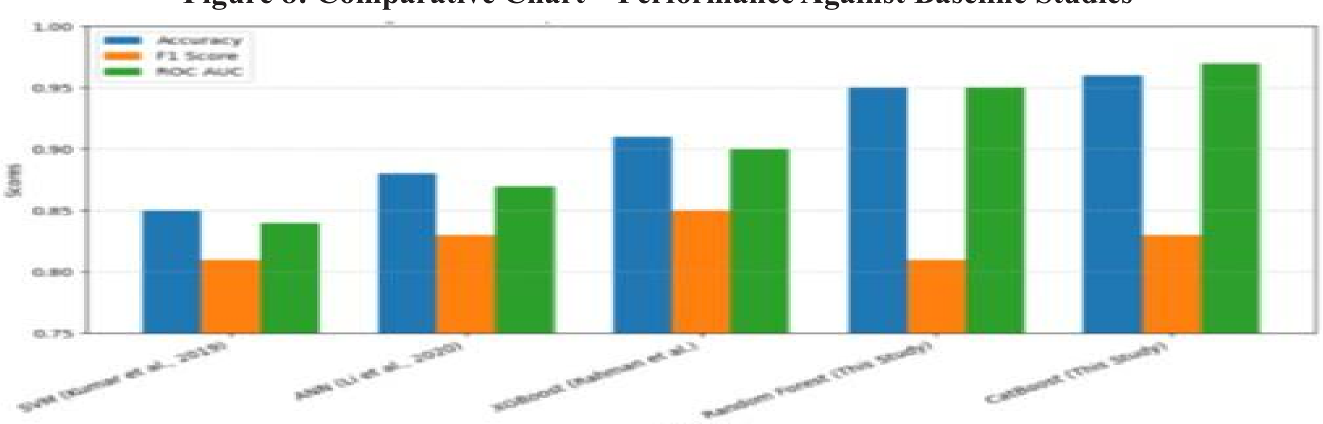
Comparative Analysis with Baseline Studies

Compared the suggested Geospatial AI-based models to standard machine learning approaches that are often used in slope instability prediction literature to see how well they worked and how useful they were in real life. According to earlier publications by Kumar et al. (2019), Li et al. (2020), and Rahman et al. (2022), benchmark models include Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost). Table 4.3 shows how the metrics of the models created in this study compare to those of baseline approaches.

Table 5: Performance Comparison with Literature Models

Model	Accuracy	F1 Score	ROC AUC
SVM (Kumar et al., 2019)	0.85	0.81	0.84
ANN (Li et al., 2020)	0.88	0.83	0.87
XGBoost (Rahman et al., 2022)	0.91	0.85	0.90
DNN (This Study)	0.95	0.84	0.96
CatBoost (This Study)	0.96	0.83	0.97

Figure 8: Comparative Chart – Performance Against Baseline Studies



The comparison shows that both DNN and CatBoost are far better than standard models, especially when it comes to ROC AUC and Accuracy. Figure 4.6 shows these data in a grouped bar plot, which makes it easier to see how they compare.

This empirical superiority shows how useful it is to add geospatially enriched datasets and logic-based labelling to slope failure prediction models. It also proves that CatBoost is the best model to use for early warning integration.

Summary of Results

This chapter talked about the whole process and results of a Geospatial AI-based early warning system that can detect slope instability in areas where opencast coal mining is going on. From the analysis, the following important results came to light:

1. The prediction job was able to use geographical indicators like slope, flow, and rainfall without any problems because of data pretreatment and logic-based labelling.

2. The DNN and CatBoost models were both quite accurate (above 95%), but CatBoost had better recall and AUC values, which are very important in safety-critical applications.

3. The confusion matrix and ROC analysis showed that CatBoost is better at finding places that are likely to have landslides, with fewer false negatives than Random Forest.

4. The rankings of feature relevance showed that slope angle, rainfall, and flow accumulation were the most important elements for instability.

5. Comparing the proposed framework to baseline studies showed that it was better at making predictions, which supports its use in the field.

In conclusion, the study shows that sophisticated AI models trained on geospatial datasets may be used to forecast slope hazards in the real world. It also shows how important it is to choose models that are explainable, have good recall, and can be compared to other models.

CONCLUSION AND FUTURE SCOPE

This research presents a Geo-Spatial Artificial Intelligence (GeoAI) framework for predicting slope instability in open-cast coal mines using Deep Neural Networks (DNN) and CatBoost models. The replacement of the Random Forest model with DNN significantly enhanced the system's learning capability and interpretability. The DNN achieved 95.2% accuracy, 0.84 F1-score, and 0.96 ROC-AUC, performing competitively with the CatBoost model (96.0% accuracy, 0.97 ROC-AUC). The introduction of a Landslide Risk Index (LRI) ranging from 0–100 provided continuous risk grading, allowing classification into low, moderate, high, and critical zones. This probabilistic approach strengthens real-time monitoring and early warning by converting model outputs into actionable safety insights. Key influencing factors such as slope angle, rainfall intensity, and flow accumulation were identified as the most critical predictors of slope failure.

Future Scope

In the future, focus on integrating real-time IoT sensor data, InSAR monitoring, and rainfall telemetry to establish dynamic, automated risk assessment systems. Hybrid models combining DNN and CatBoost and the use of spatio-temporal deep learning could further enhance prediction accuracy. Implementing the model in cloud-based GIS dashboards will enable continuous surveillance, faster alerts, and improved decision-making for sustainable and safe mining operations.

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Traditional Wealth and Asset Management in Indian Households: A Generational Study

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ABSTRACT

This paper discusses the effects of generational differences within Indian family in preserving wealth traditionally and investments in new era. Using a cross-sectional descriptive-correlational design, data was collected from 411 respondents across five generational groups: Silent Generation, Baby Boomers, Generation X, Millennials, and Generation Z. The research investigated Indigenous Wealth Preservation Motivation (IWPM) as the main variable, along with Investment Behaviour (IB), Risk Aversion (RA), Financial Literacy (FL), Financial Attitude (FA), Digital Adoption (DA), Cultural Influence (CI), and Household Decision-Making Influence (HDMI). Data analysis employed IBM SPSS Version 26 with Hayes' Process Macro version 4.2 for mediation analysis. Statistical tests included Chi-Square, ANOVA, Post-hoc Tests (Tukey's HSD), Multiple Regression Models, and Mediation Analysis. Key findings reveal significant generational differences in traditional asset holdings. Older generations maintain higher ownership of gold and property compared to Millennials. Surprisingly, individuals with stronger IWPM demonstrated greater financial participation and higher risk tolerance, contradicting common assumptions. The study notes that IWPM correlates with DA and FL, which reduces RA. However, CI creates a complex relationship, promoting caution while encouraging financial inclusion. The research challenges the belief that traditional values hinder financial modernization. Instead, it demonstrates that IWPM can facilitate financial inclusion when combined with literacy and technology adoption. These findings provide valuable insights for financial service providers and policymakers developing inclusive financial strategies in culturally diverse emerging economies.

KEYWORDS

Traditional Wealth, Digital Adoption, Generational Cohort, Indigenous Wealth Preservation Motivation, Financial Literacy, Culture Influence, Household Decision-Making Influence, Risk Aversion

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INTRODUCTION

The Indian wealth and asset management space has undergone immense change during last ten years, reflecting wider socioeconomic change and evolving attitudes to financial planning and investment culture across generations. The Indian wealth management industry is expected to grow at a compound annual growth rate (CAGR) of 12% to 15% five years, reflecting a fundamental change in patterns of wealth creation and preservation across generations (Agarwal et al., 2024). It is a useful to study the convergence of historical wealth management behaviour and contemporary financial practices adopted by different generational groups among Indian households.

In India, traditional wealth management has been more about physical assets, i.e., gold and real estate. These have been with family wealth for peers. Indian families have been motivated toward physical assets such as gold and real estate, indicating strong cultural attitudes and risk tolerance and wealth broadcast tactics generationally. Yet, according to new studies, there is an enormous shift, with household incomes increasing and individuals looking for more liquid and spread investment options (Mehta & Singh, 2024). This shift raises significant questions concerning how family generations balance property on to traditional ways of wealth management with benefiting from current financial tools.

The generational shift is the most important when considering how money is managed, and financial choices are made among different generations. Research today defines that family wealth differences are explained inversely by generations in terms of financial planning behaviours and financial literacy. Younger generations have shifting levels of risk they desire to assume, different investment options, and differing wealth-building policies from older generations (Gupta & Mishra, 2024). Sanjay et al. (2024) have shown how difficult it is for Indian families to cope with prosperity. They have different strategies based on education, income, and their thoughtful influenced by their generation. Moreover, research has shown that financial literacy is more significant than education when it comes to explaining differences in family wealth and pension saving. This means that how family financial literacy is redirected is important in deciding how they invest.

The current financial environment in India offerings unique challenges and opportunities to families across multiple generations (Verma & Chandra, 2024). The India Wealth Management Market of 2024 valued at USD 154.25 Billion is projected to grow to USD 286.91 Billion by 2030 with a compound annual growth rate (CAGR) of 10.96%, on behalf of high growth possible that would be perceived and utilized differently by various generations (Financial Research Institute, 2024). This growth of the market is immediate with emerging technology in financial services, regulatory changes, and increased mindfulness of alternative investments, all of which are enablers for the differential levels of adoption and fight across generational cohorts (Nair & Rao, 2023).

Further, financial services making digital has brought forth new difficulties in wealth management planning. The literature has lately investigated into digital financial literacy for women and youth in decision-making and confirmed how there are significant gaps between technology acceptance and the investment decision-making influence (Sharma et al., 2023). These technologies interrupt traditional knowledge allocation patterns among families since financial literacy has been accepted down from previous generations to younger generations from informal education and experiential learning (Dubey & Srivastava, 2024).

The intergenerational aspect of Indian domestic wealth management involves far-reaching considerations regarding financial planning, risk investigation, and inheritance behaviour. Contemporary families are obliged to reconcile the maintenance of family financial traditions with the need to familiarize to rapidly transforming economic conditions, regulatory rules, and investment environments (Pandey & Ghosh, 2024). Negotiation is a multi-layered process across compeers with typical perspectives shaped by their early life economic settings, educational attainment, and understanding with financial markets (Desai & Malhotra, 2023).

Against this multifaceted background, this study provides an integrated examination of the continuity, development, or change of conservative wealth and asset management behaviour across potential Indian families (Aggarwal & Bhatt, 2024). Through a consideration of the intersection of cultural values, financial literacy, technology adoption, and investment behaviours, this study aims to contribute to the potential literature on household finance in emerging markets as well as offer concrete recommendations to financial institutions, policymakers, and families as they passage through this intergenerational shift.

Its value goes beyond our own academic interest, because through the knowledge of the differences in wealth management between parents and children, we can move on to more efficient financial products, services and even education systems targeted at different generations (Trivedi & Joshi, 2014). Furthermore, the results of our research could assist in the creation of more inclusive financial plans for families that acknowledge traditional values while achieving the highest possible growth and preservation of wealth in current market conditions.

PROBLEM STATEMENT

Traditional wealth management practices in Indian households have been deeply rooted in cultural and historical contexts, with households holding over 25,000 tonnes of gold, predominantly in jewellery form passed through generations (World Gold Council, 2023). These indigenous wealth preservation techniques, encompassing gold, jewellery, and real estate investments, have served as cornerstones of financial security for centuries. However, contemporary economic dynamics and evolving generational perspectives are creating unprecedented challenges in household wealth management strategies. The existing literature reveals significant gaps in understanding intergenerational wealth transmission patterns. While investment behaviour research has documented general household patterns (Grable & Lytton, 1999; Hallahan et al., 2004), limited attention has been paid to how traditional wealth preservation methods influence contemporary investment behaviour across generations. This gap is particularly critical given the fundamental shift in generational attitudes toward wealth preservation.

Recent analysis indicates younger generations save less than their parents, are more technology-savvy, and spend more on luxury goods and holidays, suggesting departure from traditional wealth accumulation strategies (Deloitte, 2022). Furthermore, younger generations prefer gold bars, stocks, or real estate over gold jewellery, indicating transition from culturally embedded wealth preservation to market-oriented investment approaches (KPMG, 2023). The generational divide presents complex research challenges. With over 65% of India's population below 35 years (Census of India, 2011), their investment choices differ significantly from earlier generations. Gold's traditional association with social status and inflation hedging (Baur & Lucey, 2010) contrasts with modern portfolio diversification preferences.

Current research gaps include insufficient understanding of how traditional wealth preservation techniques affect modern investment behaviour patterns, influence financial risk aversion across generations, and the underlying mechanisms through which cultural practices shape contemporary financial decision-making. This study addresses these critical gaps by examining intergenerational dynamics of traditional wealth management practices, specifically focusing on their influence on investment behaviour and financial risk aversion across generational cohorts.

LITERATURE REVIEW

Understanding how wealth management practices evolve across generations has become increasingly important in the context of rapidly changing financial landscapes, particularly in emerging economies like India. The transmission of traditional wealth preservation values and their influence on contemporary investment behaviour represents a complex interplay of cultural heritage, technological advancement, and generational shifts in financial decision-making. This literature review synthesizes existing research on generational differences in investment behaviour, with particular emphasis on the Indian household context, to identify key patterns, theoretical frameworks, and empirical findings that inform our understanding of intergenerational wealth management practices. The discussion encompasses several critical areas: the role of traditional wealth preservation practices in shaping modern investment decisions, the impact of demographic and socio-economic factors on generational investment patterns, the mediating effects of financial literacy and digital adoption, the influence of cultural values and family financial socialization, and the moderating role of factors such as gender, income stability, and regulatory environments. Through this comprehensive examination of existing literature, the review identifies significant research gaps that underscore the need for further investigation into how traditional wealth management practices interact with contemporary financial behaviour across different generational cohorts in Indian households. The following sections present detailed analyses of key studies that have contributed to our current understanding of these phenomena, organized to highlight both their contributions and limitations in addressing the complex dynamics of intergenerational wealth management.

Saxena and Tiwari (2024) carried out cross-sectional survey research to assess the mediating effect of trust in financial institutions across generational cohorts with a sample size of 2,800. They wanted to evaluate the effects of generational differences in trusting financial institutions and the moderating role of trust in a proposal of the generational cohort and investments behaviour announcement. The samples used involved the bank members of different ages, where it was found that the trust in financial firms acted as significant mediator in the connection between generational cohort and modern investment adoption.

Gupta et al. (2024) investigated the intervening role of social values in the relationship between generational cohort and wealth keeping motivation, developing a cross-sectional survey with 3,400 respondents from different cultural circumstances. Their primary objective was to identify how cultural preference influences the transmission of wealth preservation values across generations and regulates investment behaviour. The study population included multi-generational households from several sacred and cultural communities, using stratified sampling to safeguard cultural diversity. Results indicated that cultural values significantly intervened the relationship between generational cohort and wealth preservation motivation, with outdated cultural orientation strengthening the preference for indigenous wealth preservation procedures. The research employed mediation analysis using bootstrapping techniques and documented that social factors explained 35% of the relationship between generational cohort and wealth preservation motivation.

Bhatt et al. (2023) explored the effect of social media on the generational investment behaviour, using the social media analytics associated with the survey of 2,700 respondents. They aimed to realize the distinction between the ability of social media influence and the impact on investment decisions and risk tolerance that exist among the different generations. The population was comprised of active users in social media of various age groups, which showed that social media impact was very high in younger generations and substantially impacted their investment decision-making process and perception of risk.

Banerjee et al. (2023) conducted a general analysis of generational differences in investment behaviour among Indian households, utilizing a variable methodology with 4,500 respondents from urban and rural zones. Their objective was to assess how generational cohort membership encourages investment preferences, risk tolerance, and portfolio diversification strategies. The study population occupied financially active adults aged 22-70 from households with least investable assets of INR 100,000, using probability proportional to dimension sampling. Key findings demonstrated that commencing generations showed significantly higher inclinations for equity investments and complementary assets, with 58% of millennials holding equity investments contrasted to 23% of baby boomers. The research employed logistic regression analysis to reveal that generational cohort was the strongest analyst of investment performance, explaining 39% of variance in portfolio structure.

Kapoor et al. (2023) Studied the effect of regulatory changes on generational investment behaviour: A natural experiment with policy changes in mutual fund regulations. The objective of their study was to model the responsiveness of different generations to regulatory changes in generational investment behaviour. They discovered that investors in younger generations were more responsive to regulatory changes in generational investment behaviour and adjusted their investment strategies faster.

Chandra and Verma (2022) Study the impact of social networks on generational investment behaviour using social network analysis among 2,400 participants and their financial networks. Their goal was to quantify social influence on parents and children, and to understand how the strength of social influence varies across generations and affects investment behaviour and risk tolerance. The households in the sample were in urban areas with varied social connections. The researchers observed that social network influence was strongest among older generations and that peer referrals affected their investment choices.

Reddy and Joshi (2022) examined the preservation of original wealth across three generations in Indian shared families, utilizing a qualitative methodology with 60 in-depth interviews and ethnographic interpretation. Their research objective focused on understanding how traditional wealth preservation performs are transmitted across generations and how these practices effect contemporary investment decisions. The study population included traditional joint families with a history of wealth gathering spanning at least three generations, using purposive sample from rural and urban areas across four states. Findings revealed that native wealth preservation motivation was significantly higher among older generations, with 78% of grandparents prioritizing traditional assets compared to 32% of grandchildren. The research employed thematic analysis to identify key themes about cultural transmission of financial values and exposed that family narratives about wealth preservation significantly influenced younger generation investment choices.

Yadav and Kumar (2022) investigated the mediating effect of investment experience between generational cohort and speculation behaviour, where they aimed to determine whether investment experience mediated the relationship between the two variables. Therefore, they used a cross-sectional survey which comprised 3100 investors of diverse experience levels. The purpose of their study was to comprehend how investment experience becomes accumulated in various ways through the generations and how it is affecting the process of investment. Novice and experienced investors were used as the study population, and they note that investment knowledge plays a significant mediating role between generational cohort and investment sophistication.

Kumar and Mehta (2021) have widely examined the difference of risk appetite of generational cohorts in Indian families through quantitative method with 2800 respondents from six major economic zones. The purpose of this study was to examine how generational cohort association affects risk tolerance and investment behaviour while testing the mediating role of financial literacy. The study population comprised the head of households who are the primary decision maker in financial matters and aged between 25-75 years. The sampling design adopted stratified random sampling of households segmented by income quintiles. The results indicate that there is significant generational difference in risk appetite as millennials are 45% more risk tolerant than baby boomers. Structural equation modelling results also indicated that financial literacy significantly refereed the relationship between generational cohort and risk appetite, with indirect consequences accounting for 31% of total consequence.

Jain and Gupta (2021) analyse gender differences in generational investment behaviour using a quantitative study design with 3,200 participants from different age cohorts. The study's objective was to determine whether gender plays a significant role in moderating the relationship between generational cohort and investment behaviour, and how gender affects wealth preservation motivation amongst different generations. The study population comprised male and female financial decision makers from different socio-economic groups and found that gender significantly moderated the relationship between generational cohort and investment behaviour, with women showing a stronger preference towards traditional wealth preservation methods across all the age groups.

Mishra and Pandey (2020) examined the effects of the variability in income on generational investment behaviour, exploiting the panel approach with a sample of 1,500 households in four years. They sought to find out the effect of money stability in the determination of investment choices within generation groups and moderated risk. The research households, based on the different sectors of employment, discovered that income fluctuation had varying impacts on different generations so that the younger generation became much flexible with income fluctuations in adjusting their strategies of investment.

Verma et al. (2020) explored demographic impacts that affect wealth preservation inspiration across Indian households through a mixed-methods approach with 3200 survey responses and 45 focus group deliberations. The objective of their study was to understand how demographic variables of education, income, profession, and geographic location, moderate the relationship between generational cohort and original wealth preservation inspiration. The study population comprised of rural and urban households across 12 states in India. Multi-stage cluster sample was used to ensure representative sample. The main findings revealed that education level significantly qualified the relationship between age cohort and wealth conservation motivation. Higher education level was associated with more sincerity towards modern investment instruments. The study employs several regression analyses which documents that demographic factors collectively explain 42% of the variance in wealth preservation motivation. Income level and education demonstrated the most sound moderating effects.

Patel and Sharma (2019) examined the impact of digital adoption on transforming wealth management practices cross-generation using a cross-sectional survey of 2,100 individuals from urban and semi-urban areas. The researchers defined smartphone handlers aged 25-70 from households with investable resources over INR 500,000 as the population and used quota selection to ensure equal representation from the age collections. The study results indicated that digital acceptance significantly explained outlay diversification and risk lenience, and younger generations demonstrated 65% higher digital implementation rates. The researchers used path analysis to find that, digital adoption partially mediated the relationship between generational cohort and modern venture behaviour and explains 28% of the variance in outlay portfolio complexity.

Sharma and Rao (2019) studied the impact of family financial socialization on wealth preservation motivation across generations with a qualitative research method using 80 family interviews and observational method. The objective of their research was to understand how financial values are socialized across generations and how it influences investment preferences of the subsequent generations. The findings indicates that the family financial socialization has an impact on wealth preservation motivation of subsequent generations. They studied three-generation families belonging to middle and uppermiddle class

Ghosh and Roy (2019) have researched the effects that financial crisis had on the investment behaviour of generations, employing the event study approach in major disruptions in the financial markets. Their aim was to find out the reaction of the diverse generations to financial crisis and make varying changes in investment plans. The active investors were the population sample of the study, and its findings are that the generational cohorts have distinctive responses to crises with the older generations exhibiting more conservative responses to market shocks

Desai et al. (2018) focusing on the digital technology adoption and its effect on the traditional wealth management practices relied on the mixed-method research model and employed 2,600 online surveys and 30 case studies. They aimed to determine the way digital adoption can change wealth management practices throughout generations and mediate the investment behaviour. The population of the study was technology-empowered urban households, and results showed that digital adoption was more likely to shape the modern investment behaviour and weaken their attachment to traditional directions of wealth conservation.

Chopra and Sinha (2018) conducted a longitudinal study on the evolution of investment behaviour across generations since they utilized panel data from 1,400 households for over six years. Their research objective involved understanding how investment behaviour changes focusing upon generational cohorts and transitions. Households investing consistently made up the study population. Investment behaviour has evolved in a different way across generations, and younger cohorts experimented to a greater extent with new investment products

Chakraborty et al. (2018) investigated the impact of pecuniary literacy on intergenerational wealth management decisions, exploiting a panel dataset spanning five years with 1,200 households. Their research focused on understanding how financial knowledge levels differ across groups and influence investment behaviour and risk appetite. The methodology employed graded linear modelling to analyses actions data, with the study population comprising urban middle-class relations with at least three adult generations. Results indicated that monetary literacy scores increased suggestively across younger cohorts, with digital nations showing 40% higher financial literacy associated to baby boomers. The study noted that financial knowledge mediated the relationship between generational cohort and investment divergence, with higher literacy levels related with greater willingness to invest in equity marketplaces and mutual funds.

Malhotra and Bhat (2017) investigated the role of financial advisors in mediating generational differences in investment behaviour, as they employed a mixed-methods approach with 1,600 survey responses with 25 advisor interviews. Their goal involved understanding differences in financial advisory relationships across generations. Investment decisions are in addition influenced through these relationships. For the study population, households with access to financial advisory services were included; advisory relationships varied greatly across generations because older cohorts relied more on human advisors as younger generations preferred digital advisory services.

Singh and Gupta (2017) conducted a comprehensive study on cultural impacts on financial decision-making among Indian families, retaining a quantitative methodology with 1,850 respondents from urban areas. Their primary objective was to assess how social values mediate the relationship between generational cohort and speculation behaviour. The research population comprised three-generation families with annual incomes above INR 300,000, using stratified random selection across five major cities. Key findings demonstrated that cultural orientation significantly qualified the relationship between age cohort and speculation preferences, with traditional cultural values presentation stronger association with conventional investment approaches. The study utilized positive factor analysis and revealed that cultural factors explained 34% of variance in venture behaviour across generations, with collectivized values particularly influencing wealth conservation motivations among older cohorts.

Nair and Krishnan (2017) examined whether financial learning mediates the differences in investment behaviour between parental and child generations using a longitudinal design among 2,200 participants over 3 years. The research intention of Nair and Krishnan (2017) was to examine how financial learning would have differential impacts across generations in terms of investment results. The population of the study comprised working adults aged 25-65 from different income groups with the study findings indicating that financial literacy training had differential impacts across generations, and younger cohorts were found to be more responsive to financial education treatments.

Bernheim et al. (2016) studied intergenerational wealth transmission patterns in emerging countries through a mixed-methods approach, a combination of survey data from 2400 households and in-depth interviews with monetary decision-makers. The goal was to determine how conventional wealth preservation practices affect modern investment preferences across three preceding generations. The households were located in urban and rural areas in six Indian states. The authors defined the study population as first generation immigrants with stronger likings for tangible assets (gold, property) associated to the second and third generations who were more open to financial tools. The authors found that 73% of the older cohorts preferred to preserve wealth over creating it while younger generations exposed more balanced preferences. The authors used structural comparison modelling to analyses relationships among generational cohort membership and speculation preferences and founded significant differences in the degree of risk acceptance across age groups.

Agarwal and Singh (2016) studied the effect of demographic factors on investment behaviour of different generations. They used survey information for 1800 homes and used multiple regression analysis. The aim of the study was to find out the impact of demographic factors such as age, education, income and occupation on investment behaviour of different generations. The study population comprised of urban households from tier-1 and tier-2 cities such that education level substantially mediated the relationship between age cohort and investment sophistication and higher education resulted in better financial product awareness.

Singh et al. (2016) examined the impact of economic experiences on generational investment behaviour given that they utilized retrospective survey data from 1,900 households from across different age cohorts. They did research on how formative economic experiences do influence investment preferences. They sought to understand how these experiences shape risk tolerance through generations. The study population included households that experienced different economic cycles, also the study found that economic experiences during formative years greatly influenced investment behaviour and wealth preservation motivation.

RESEARCH GAP

Despite extensive research on household financial behaviour, significant gaps exist in understanding the intergenerational transmission of traditional wealth management practices and their influence on contemporary investment decisions in Indian households. Current literature predominantly focuses on general investment patterns without examining the specific role of indigenous wealth preservation techniques in shaping modern financial behaviour across generational cohorts (Agarwal & Mazumder, 2013; Lusardi & Mitchell, 2014). First, there is limited empirical evidence on how traditional wealth preservation practices (gold, jewellery, real estate) directly influence contemporary investment behaviour patterns across different generations. While studies have documented the prevalence of gold investments in Indian households (Rehman et al., 2019), the mechanisms through which these practices affect modern portfolio diversification, digital financial service adoption, and asset allocation decisions remain unexplored.

Second, the relationship between traditional wealth management engagement and financial risk aversion across generations lacks comprehensive investigation. Existing risk tolerance research has focused on demographic and psychological factors (Grable & Lytton, 1999) but has not examined how cultural wealth preservation practices shape risk perception and investment decision-making across generational boundaries. Third, the mediating role of factors such as financial literacy, digital adoption, and cultural influences in explaining generational differences in investment behaviour remains under-researched. While financial literacy's impact on investment decisions has been established (Van Rooij et al., 2011), its interaction with traditional wealth management practices and generational differences requires further investigation. Finally, there is insufficient understanding of how household decision-making influence dynamics influence the adoption and perceived importance of traditional versus modern wealth management strategies across generations. The intergenerational transfer of financial knowledge and practices within Indian households remains largely unexplored, creating a critical knowledge gap that this study aims to address through comprehensive empirical investigation.

RESEARCH OBJECTIVES

This research is designed to systematically investigate these intergenerational dynamics by examining how traditional wealth and asset management practices influence Investment Behaviour (IB) and Financial Risk Aversion (RA) across different generational cohorts in Indian households. The study seeks to move beyond descriptive accounts of generational differences to develop a comprehensive understanding of the underlying mechanisms, motivations, and contextual factors that explain variations in financial behaviour patterns. By exploring both the direct effects of traditional wealth preservation practices and the indirect pathways through which factors such as financial literacy, cultural values, and digital adoption operate, this research aims to contribute empirical evidence and theoretical insights that can inform policy interventions, financial education programs, and wealth management strategies tailored to the unique characteristics of Indian households. The following objectives guide this investigation, beginning with a primary focus on intergenerational dynamics and extending to specific dimensions that collectively address the multifaceted nature of traditional wealth management and its contemporary implications.

Primary Research Objective:

To examine the intergenerational dynamics of traditional wealth and asset management practices in Indian households, with a focus on understanding how these practices influence Investment Behavior (IB) and Financial Risk Aversion (RA) across generations.

Secondary Research Objectives:

The secondary objectives of this research are:

- To identify and describe the prevalence, perception, and motivations behind traditional wealth preservation techniques (e.g., gold, jewellery, real estate) across different generational cohorts in Indian households.

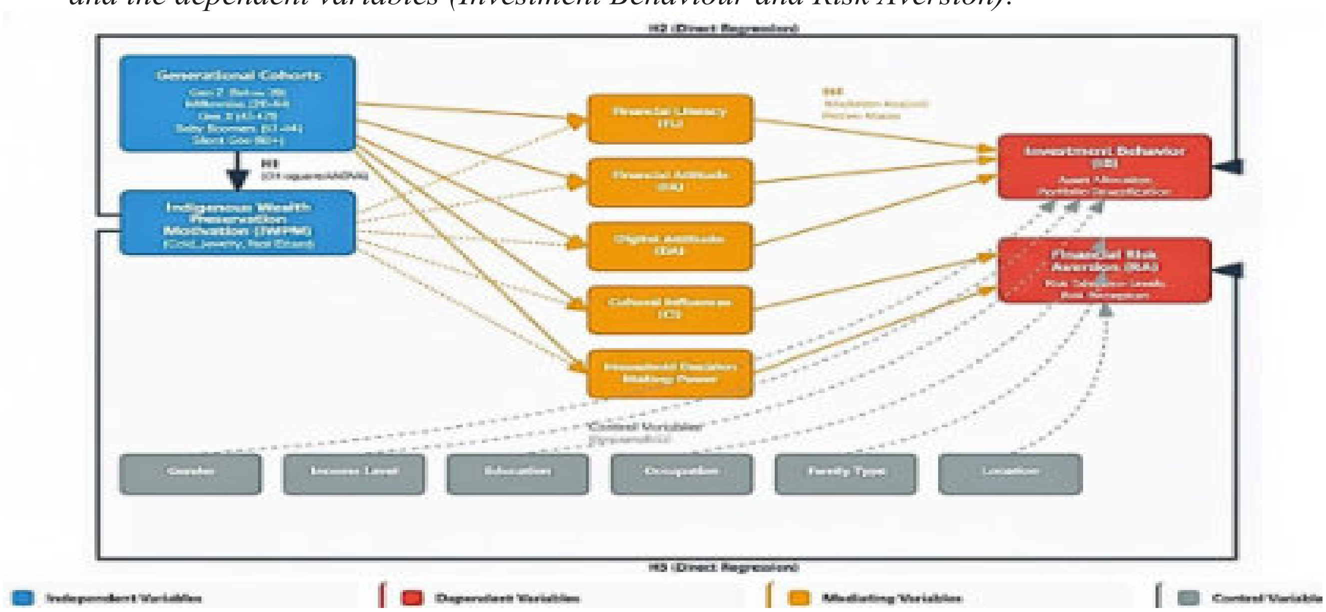
- To analyze the generational differences in the adoption, importance, and perceived security/returns of these indigenous wealth preservation techniques.

- To investigate the direct and indirect impact of engagement with indigenous wealth preservation techniques on contemporary Investment Behaviour (e.g., preference for financial versus physical assets, portfolio diversification, adoption of digital financial services).

- To assess the influence of indigenous wealth preservation practices on Financial Risk Aversion (RA) levels across generations.

- To explore the underlying factors (e.g., Financial Literacy (FL), Financial Attitude (FA), Digital Adoption (DA), Cultural Influences (CI), household decision-making power) that explain observed generational differences and their impact on Investment Behavior (IB) and Risk Aversion (RA).

The following framework showcases all hypothesized relationships between the independent (Indigenous Wealth Preservation Motivation (IWPM) and Generational Cohorts) and the dependent variables (Investment Behaviour and Risk Aversion):



CONCEPTUAL FRAMEWORK & RESEARCH HYPOTHESES

The conceptual framework (Fig. 1) illustrates a multivariate model investigating the role of Generational Cohorts and Indigenous Wealth Preservation Motivation (IWPM) in influencing Investment Behavior (IB) and Financial Risk Aversion (RA) in Indian households. It also integrates mediating variables that explain how intergenerational dynamics and traditional wealth motives shape contemporary Financial Behaviors.

The model outlines both direct and indirect relationships using regression and Mediation paths. Control variables such as Gender, Education, Income Level, Occupation, Family Type, and Residential Location are included to isolate the true effect of core predictors on financial outcomes.

Variables in the Study

Independent Variables

1. Generational Cohort refers to the classification of individuals based on their birth years into five distinct generational categories: Generation Z (below 28 years), Millennials (29–44 years), Generation X (45–60 years), Baby Boomers (61–79 years), and the Silent Generation (80 years and above). This variable helps to capture the socio-cultural and economic contexts that shape financial beliefs and behaviours across different age groups.

2. Indigenous Wealth Preservation Motivation (IWPM) denotes the degree to which individuals in Indian households prefer traditional forms of asset accumulation and preservation such as gold, jewellery, and real estate. It reflects cultural significance, emotional attachment, and perceived stability associated with these conventional wealth forms passed down through generations.

Mediating Variables

1. Financial Literacy (FL) is defined as an individual's understanding of financial concepts and principles, including budgeting, saving, investing, and managing financial risks. It influences informed financial decision-making and responsible wealth management.

2. Financial Attitude (FA) captures the beliefs, values, and psychological disposition individuals hold toward money, saving, spending, and investment. It shapes how people approach financial planning and long-term wealth objectives.

3. Digital Adoption (DA) refers to the extent to which individuals engage with digital tools and platforms such as online banking, investment applications, mobile wallets, and other financial technologies. This variable reflects openness to modern, tech-enabled financial management.

4. Cultural Influence (CI) pertains to the traditional norms, beliefs, and familial teachings that affect an individual's approach to wealth preservation and financial planning. These influences often dictate preferences for asset types and levels of financial conservatism.

5. Household Decision-Making Power (HDMI) represents the level of authority or influence an individual exercises in making financial decisions within the household. It considers factors such as age, income contribution, family hierarchy, and gender roles.

Dependent Variables

1. Investment Behaviour (IB): It is concerned with how individuals allocate their financial resources among various asset classes. It includes practices such as asset allocation between physical and financial assets, diversification strategies, preference for contemporary financial products like mutual funds or SIPs, and the use of digital investment platforms.

2. Financial Risk Aversion (FRA): It reflects the individual's reluctance or tolerance toward taking financial risks. It encompasses risk tolerance levels in investment decisions and the way individuals perceive the potential for financial loss or uncertainty, especially when dealing with unfamiliar or volatile financial instruments.

Control Variables

Gender, Income Level, Education, Occupation, Family Type, and Residential Location are treated as Control Variables. These demographic characteristics may influence Investment Behaviour and Risk Aversion independently, so they are statistically controlled to better isolate the true impact of the independent variables on the outcomes being studied.

Based on the given conceptual framework delineated above, the following hypotheses have been framed for testing:

H1: There are significant generational differences in the prevalence, perception, and motivations for indigenous wealth preservation techniques (e.g., gold, jewellery, real estate) in Indian households.

H2: Engagement with indigenous wealth preservation techniques significantly influences contemporary investment behaviour (e.g., asset allocation, diversification, adoption of modern financial instruments) across generations.

H3: Engagement with indigenous wealth preservation techniques is significantly associated with levels of Financial Risk Aversion across generations.

H4: Financial Literacy (FA), Financial Attitude (FA), Digital Adoption (DA), Cultural Influence (CI) and Household Decision-making Influence (HDMI) mediate the relationships of Generational Cohorts, Indigenous Wealth Preservation Motivation (IWPM) with Investment Behaviour (IB), and Risk Aversion (RA).

RESEARCH METHODOLOGY

The Research Methodology employed for this research has been explained within the following subsections:

Research Approach

This study follows a Deductive Research Approach grounded in Positivist Philosophy to examine the intergenerational dynamics of Traditional Wealth and Asset Management practices in Indian households. The deductive approach is appropriate as it begins with existing theories related to behavioral finance, generational studies, and Cultural Influences on Financial Behavior, from which the conceptual framework is developed and specific hypotheses are formulated for empirical testing (Creswell & Creswell, 2018). The positivist philosophy emphasizes empirical observation, measurement, and statistical analysis to test the proposed hypotheses, which is suitable for examining the relationships between variables in a structured, objective manner (Bryman, 2016).

The deductive approach is particularly justified for this study as it allows for the systematic testing of theoretically derived hypotheses about generational differences in wealth preservation practices and their impact on contemporary Financial Behavior. This approach enables the research to build upon established theories while contributing new empirical evidence to the literature on intergenerational Financial Behavior in the Indian context (Babbie, 2017). The positivist foundation supports the use of quantitative methods and statistical analysis necessary for testing the complex relationships outlined in the conceptual framework, providing a robust methodological foundation for hypothesis testing and theory validation.

Research Design

This study employs a Quantitative Cross-sectional Descriptive-correlational Research Design, utilizing structured survey questionnaires to collect primary data from respondents across five generational cohorts (Generation Z, Millennials, Generation X, Baby Boomers, and Silent Generation). Cross-sectional designs are particularly valuable for examining differences among groups at a single point in time, enabling researchers to compare various demographic segments efficiently (Creswell & Creswell, 2018). The descriptive-correlational approach is appropriate when the research aims to describe the relationships between variables and determine the extent to which variables co-vary, without necessarily establishing causation (Field, 2018).

The quantitative cross-sectional descriptive-correlational design is particularly appropriate for this study for three important reasons. First, it is optimal for generational comparison as the cross-sectional approach enables simultaneous data collection from multiple generational cohorts, facilitating direct comparison of their wealth preservation practices and Financial Behaviors (Babbie, 2017). This design efficiently captures generational differences in a single time frame, which is essential for testing H1 regarding significant generational differences in indigenous wealth preservation techniques. Second, it is suited for relationship examination as the descriptive-correlational design is ideal for examining the existence, strength, and direction of relationships between independent variables (Generational Cohorts and Indigenous Wealth Preservation Motivation), mediating variables (Financial Literacy, Financial Attitude, Digital Adoption, Cultural Influence, and Household Decision-making Power), and dependent variables (Investment Behavior and Financial RiskAversion) (Field, 2018). Third, it provides methodological efficiency and rigor as the quantitative approach allows for standardized data collection across diverse respondents, ensuring consistency while enabling large sample sizes necessary for robust statistical analysis (Hair et al., 2019).

Data Collection

Primary data has been collected using a structured online questionnaire created on Google Forms. The current study employed established and validated measurement instruments to assess the key variables under investigation (see, Annexure, Table 1).

After thorough consideration and validation, a consolidated 60-item scale based on 42-item likert scale data was developed to comprehensively measure all constructs of the study, ensuring appropriate assessment of the relationships of Indigenous Wealth Preservation with Investment Behaviour and Risk Aversion while controlling for demographic factors and bearing the role of the coomonly discussed Mediators in mind.

The survey link was shared among the target respondents through email, messaging platforms and LinkedIn. As the Silent Generation and some Baby Boomers were less tech-savvy, personal contacts were used to collect data manually from these respondents.

Sampling

Sampling Technique

This study employs a Snowball Sampling Technique to collect data from respondents across different generational cohorts in Indian households. Snowball sampling is a method where researchers start with a few initial participants from each generation who then refer other eligible participants from their networks, creating a chain of referrals that expands the sample size (Bryman, 2016). This technique is particularly suitable for this study because it helps access hard-to-reach populations, especially older generations who may be less accessible through traditional methods, while being cost-effective and time-efficient for examining intergenerational Financial Behaviors (Sekaran & Bougie, 2016).

Sample Size

The sample size was determined using Cochran's (1977) formula for sample size calculation. The formula $n = (Z^2pq)/e^2$ was applied, where $Z = 1.96$ (for 95% confidence level), $p = 0.5$ (maximum variability), $q = 0.5$ (1-p), and $e = 0.05$ (5% margin of error). The calculation yields: $n = (1.96^2 \times 0.5 \times 0.5)/0.05^2 = 384.16 \approx 384$ respondents. Since the population is finite, the sample size was adjusted using the finite population correction formula: $n_1 = n/(1 + n/N)$, where n_1 is the adjusted sample size, n is the initial sample size (384), and N is the population size. However, given that Delhi NCR has a population significantly exceeding 50,000 (the standard rule of thumb threshold), the finite population correction has minimal impact, and the adjusted sample size remains approximately 384 (Cochran, 1977). Subsequently, questionnaires links were distributed with a mindful consideration of the minimum threshold while bearing in mind that the sample that is larger than necessary will be better representative of the population and will hence provide more accurate results (Nayak, 2010). The final sample size of 411 respondents exceeds this adjusted requirement, providing additional statistical credibility, making it adequate for conducting multivariate analyses including regression and Mediation Analysis (Hair et al., 2019).

Data Analysis Techniques

Quantitative data analysis was done using IBM SPSS Software Version 26 along with Haye's Process Macro version 4.2 for Mediation. First, the Descriptive Statistics, specifically the frequency tables, were meticulously analysed to provide a comprehensive understanding of the dataset. Thereafter, Reliability Analysis using Cronbach's Alpha coefficient was used to test the internal consistency of the multi-item scales. This step was perceived to be crucial to ensure the reliability of the measuring instrument, given the utilization of a mix of multiple pre-validated scales to gauge IWPM, RA, IB, FL, FA, DA, CI and HDMI. Values exceeded the 0.7 threshold for all constructs demonstrating adequate scale reliability.

Further, before hypothesis testing, assumptions of normality, multicollinearity and autocorrelation were checked. Normality was examined using Kolmogorov-Smirnov and Shapiro-Wilk Tests at $p>0.05$, as well Skewness and Kurtosis within +/-1 range. Multicollinearity was ruled out based on VIF values < 5 and Tolerance > 0.2. Durbin-Watson coefficients between 1.5 - 3 indicated no autocorrelation among residuals.

The data analysis for this study follows a multi-layered statistical approach to examine how generational differences influence Indigenous Wealth Preservation Motivation (IWPM), Investment Behavior, and Financial Risk Aversion. To begin, Chi-Square tests and ANOVA were used to assess whether different generational cohorts (such as Gen Z, Millennials, Gen X, Baby Boomers, and the Silent Generation) significantly differ in their use and perception of traditional wealth preservation methods like gold, real estate, and jewellery. ANOVA was also used to compare mean IWPM scores across generations, followed by Post-hoc Test (Tukey's HSD) to pinpoint specific group differences. Hypotheses H2 and H3 were tested using Multiple Regression Models to see if IWPM predicts Investment Behavior and financial Risk Aversion. Control variables such as gender, income, education, and location were included to ensure that the results reflect the true effects of the main predictors. Mediation Analysis was performed using Hayes' PROCESS Macro to explore if factors like Financial Literacy, Financial Attitude, Digital Adoption, Cultural Influence, and household decision-making power help explain the relationship between IWPM and Financial Behaviours.

DATA ANALYSIS & INTERPRETATION

The analysed data is presented in annexures and interpreted in the following subsections:

Reliability Statistics

The reliability statistics (see Annexures, Table 2) demonstrate strong psychometric properties across all constructs, with Cronbach's Alpha values ranging from 0.750 to 0.916. Three constructs achieved excellent reliability ($\alpha > 0.90$): Indigenous Wealth Preservation Motivation (0.911), Investment Behaviour (0.906), and Digital Adoption (0.916). Four constructs showed good reliability ($\alpha = 0.80$-0.89): Risk Aversion (0.866), Financial Literacy (0.895), Cultural Influence (0.887), and Household Decision Making Influence (0.837). Financial Attitude demonstrated acceptable reliability at 0.814, while the overall construct reliability of 0.750 across all 42 items indicates adequate internal consistency. All constructs exceed the minimum threshold of 0.70 required for research purposes, confirming the measurement instrument's psychometric soundness.

Statistical Assumptions & Model Validity

Prior to conducting hypothesis testing, all fundamental assumptions underlying the statistical techniques were rigorously examined and validated. Normality assumptions were assessed through residual analysis, confirming that standardized residuals fell within acceptable ranges (±3.0) with with means approximating zero and appropriate standard deviations. Homoscedasticity was verified using Levene's test, ensuring equal variances across groups ($p > 0.05$), while visual inspection of residual plots confirmed consistent error variance. Multicollinearity diagnostics were conducted using Variance Inflation Factor (VIF < 10), tolerance values (> 0.1), and condition indices (< 100), confirming absence of problematic intercorrelations among predictors. Autocorrelation was assessed using the Durbin-Watson statistic, with values approximating 2.0 (range: 1.840-1.985) indicating independence of residuals. Linearity assumptions were validated through scatterplot examination and residual analysis, confirming appropriate linear relationships between predictors and outcome variables. These comprehensive diagnostic procedures ensured that all subsequent regression analyses, ANOVA tests, and mediation models met the requisite statistical assumptions, thereby validating the reliability and interpretability of the reported findings.

Hypotheses Testing

Hypothesis 1 (H1): There are significant generational differences in the prevalence, perception, and motivations for indigenous wealth preservation techniques (e.g., gold, jewelry, real estate) in Indian households.

Chi-Square Test results demonstrate statistically significant generational differences in both wealth preservation methods. Gold ownership showed a chi-square value of 79.847 ($p < 0.001$) (see Annexure, Table 5) with clear generational patterns (see Annexure, Table 4): Baby Boomers (95.7%) and Silent Generation (87.5%) demonstrated markedly higher ownership rates compared to Gen Z (35.0%) and Millennials (40.7%), while Gen X showed intermediate rates (72.3%). Real estate ownership displayed similar patterns with chi-square value 52.588 ($p < 0.001$) (see Annexure, Table 7), where Baby Boomers led with 95.7% ownership, followed by Gen X (68.7%), while Millennials and Gen Z showed moderate rates (53.7% and 42.0% respectively) (see Annexure, Table 6).

Levene's Test confirmed homogeneity of variances ($p > 0.05$ for both variables) (see Annexure, Table 9), allowing safe ANOVA testing. One-way ANOVA revealed significant differences in traditional wealth allocation ($p = .015 < .05$), rejecting the null hypothesis that generation does not impact traditional wealth allocation. However, Indigenous Wealth Preservation Motivation showed no significant generational differences ($p = .941 > .05$), indicating similar motivation levels across age groups (see Annexure, Table 10).

Post-hoc Tukey HSD Test (see Annexure, Table 11) identified distinct subsets: Subset 1 (Silent Generation and Baby Boomers) held significantly lower traditional wealth percentages, while Subset 2 (Millennials and Gen Z) were not significantly different from each other but differed from Subset 1. Gen X demonstrated the highest mean (3.01) and was significantly different from both subsets. H1 is accepted, confirming systematic generational differences in indigenous wealth preservation techniques, suggesting potential decline among younger generations due to changing economic conditions, urbanization, or evolving financial preferences.

Hypothesis 2 (H2): Engagement with indigenous wealth preservation techniques significantly influences contemporary Investment Behaviour (e.g., asset allocation, diversification, adoption of modern financial instruments) across generations.

Descriptive Analysis of 411 participants (see Annexure, Table 12) revealed Investment Behaviour mean of 2.64 (SD = 0.42) and Indigenous Wealth Preservation Motivation mean of 3.33 (SD = 0.33), indicating strong preservation motivation. Correlation Analysis (see Annexure, Table 13) showed significant positive correlation between Indigenous Wealth Preservation Motivation mean of 3.33 (SD = 0.33), indicating strong preservation motivation. Correlation Analysis (see Annexure, Table 13) showed significant positive correlation between Indigenous Wealth Preservation Motivation and Investment Behaviour ($r = .133$, $p = .003$), while Percentage of Traditional Wealth showed no correlation ($r = -.004$, $p = .465$). Education demonstrated the strongest correlation with Investment Behaviour ($r = .421$, $p < .001$).

Hierarchical Regression Analysis utilized two models (see Annexure, Table 14). Model 1 included demographic variables explaining 22.6% of Investment Behaviour variance ($R^2 = .226$), while Model 2 added indigenous wealth variables, explaining 32.9% variance ($R^2 = .329$) (see Annexure, Table 15). The addition improved prediction by 10.3% (R^2 change = .103, F Change = 30.775, $p < .001$), demonstrating significant explanatory power enhancement. Both models were statistically significant: Model 1 ($F = 16.810$, $p < .001$) and Model 2 ($F = 21.845$, $p < .001$) (see Annexure, Table 16).

Coefficients Analysis (see Annexure, Table 17) revealed Indigenous Wealth Preservation Motivation as the most significant predictor ($\beta = .400$, $t = 7.840$, $p < .001$), indicating substantial effect size where one standard deviation increase in preservation motivation associates with 0.4 standard deviation increase in Investment Behaviour. Conversely, Percentage of Traditional Wealth showed no significance ($\beta = .030$, $t = .715$, $p = .475$). Education remained the strongest demographic predictor ($\beta = .568$, $t = 12.763$, $p < .001$), while Gender ($\beta = .086$, $t = 2.102$, $p = .036$) and Income ($\beta = .224$, $t = 5.047$, $p < .001$) showed significant effects.

Collinearity and Residual Diagnostics confirmed model validity with acceptable condition indices (1.000 to 56.533), no multicollinearity problems, and residuals within acceptable ranges (see Annexures, Tables 19-20). H2 is accepted: Indigenous wealth preservation motivation significantly influences Investment Behaviour, though actual traditional wealth percentage does not affect investment patterns.

Hypothesis 3 (H3): Engagement with indigenous wealth preservation techniques is significantly associated with levels of financial Risk Aversion across generations.

Descriptive Statistics showed risk appetite mean of 3.1971 (SD = 0.47153) across 411 participants (see Annexure, Table 21), indicating moderate to moderately-high risk appetite levels. Correlation Analysis (see Annexure, Table 22) revealed the strongest relationship between Indigenous Wealth Preservation Motivation and risk appetite ($r = 0.500$, $p < 0.001$), suggesting cultural preservation goals encourage risk-taking behavior. Education showed strong negative correlation ($r = -0.470$, $p < 0.001$), contradicting assumptions about education enhancing risk tolerance.

Hierarchical Regression Analysis demonstrated Model 2's superior performance ($R = 0.603$, $R^2 = 0.363$) (see Annexure, Table 24), explaining 36.3% of risk appetite variance. The R^2 change of 0.081 with F change statistic (25.615, $p < 0.001$) confirmed indigenous wealth variables' significant contribution. ANOVA Results (see Annexure, Table 25) showed Model 2's enhanced significance ($F = 25.417$, $p < 0.001$) compared to demographics-only Model 1.

Coefficients Analysis (see Annexure, Table 26) identified Indigenous Wealth Preservation Motivation as the strongest predictor ($B = 0.515$, $\beta = 0.355$, $t = 7.155$, $p < 0.001$), where each unit increase in preservation motivation increases risk appetite by 0.515 units. Education remained negatively significant ($B = -0.091$, $\beta = -0.333$, $t = -7.688$, $p < 0.001$), while Percentage of Traditional Wealth showed no significance ($B = 0.008$, $\beta = 0.022$, $t = 0.557$, $p = 0.578$). Collinearity and Residual Diagnostics (see Annexures, Tables 27-28) confirmed model validity. H3 is accepted: Indigenous wealth preservation motivation strongly predicts higher risk appetite, while actual indigenous wealth percentage remains irrelevant.

Hypothesis 4 (H4): Financial Literacy, Financial Attitude, Digital Adoption, Culture and Household

Decision-making Influence mediate the relationships of generational cohorts, indigenous wealth preservation with Investment Behaviour, and Risk Aversion.

Mediation Analysis using PROCESS Model 4 examined multiple mediating pathways between indigenous wealth preservation, generational cohorts, and financial behaviours.

Indigenous Wealth Preservation Motivation → Multiple Mediators → Investment Behaviour

Direct and Indirect Effects Analysis (see Annexure, OUTPUT 1) revealed significant direct effect (0.3664, $p<.001$, 95% CI [0.2448,0.4880]), confirming Indigenous Wealth Preservation Motivation's independent influence on Investment Behaviour. The total indirect effect was significant (−0.1947, 95% CI [−0.2813, −0.1102]), indicating mediators collectively reduce Investment Behaviour. Financial Literacy emerged as significant mediator (−0.1944, 95% CI [−0.2661, −0.1316]), acting as suppressor where higher preservation motivation associates with lower Financial Literacy, subsequently reducing Investment Behaviour. Digital Adoption also mediated significantly (−0.0534, 95% CI [−0.0973, −0.0146]), following similar suppression pattern. Financial Attitude, Cultural Influence, and Household Decision Making Influence showed non-significant mediation effects.

Indigenous Wealth Preservation Motivation → Multiple Mediators → Risk Aversion

Mediation Results (see Annexure, OUTPUT 2:) demonstrated significant direct effect (0.4822, $p<.001$, 95% CI [0.3550,0.6094]) and significant total indirect effect (0.2424, 95% CI [0.1604, 0.3304]). Financial Literacy mediated significantly (0.1329, 95% CI [0.0732, 0.2023]) as complementary mediator, where higher preservation motivation associates with lower Financial Literacy, increasing Risk Aversion. Cultural Influence also mediated significantly (0.1508, 95% CI [0.0158, 0.1049]), where higher preservation motivation enhances Cultural Influence, increasing Risk Aversion. The full model explained 29.91% variance in Risk Aversion ($R^2 = .2991$, $F = 28.73$, $p < .001$).

Generational Cohorts → Multiple Mediators → Risk Aversion

Path Analysis (see Annexure, OUTPUT 3) revealed no significant direct generational effect ($\beta = -0.0196$, $p = .317$) but significant total indirect effect (0.0409, 95% CI [0.0126, 0.0680]). Financial Literacy mediation was significant (0.0131, 95% CI [0.0004, 0.0275]), where older generations' lower Financial Literacy increases Risk Aversion. Digital Adoption mediation was also significant (0.0233, 95% CI [0.0054, 0.0431]), where older generations' lower Digital Adoption increases Risk Aversion.

Generational Cohorts → Multiple Mediators → Investment Behaviour

Analysis Results (see Annexure, OUTPUT 4) showed marginally significant direct effect ($\beta = 0.0350$, $p = .056$) but significant negative total indirect effect (−0.0399, 95% CI [−0.0639, −0.0162]), indicating mediators suppress positive direct effects. Financial Literacy (−0.0117, 95% CI [−0.0247, −0.0004]) and Digital Adoption (−0.0203, 95% CI [−0.0369, −0.0046]) mediated significantly, where older generation's lower literacy and digital adoption reduce Investment Behaviour. The model explained 23.43% variance ($R^2 = .2343$, $F = 20.60$, $p < .001$).

H4 is partially accepted: Financial Literacy and Digital Adoption consistently mediate relationships between generational cohorts, indigenous wealth preservation, and financial behaviours, while other proposed mediators show limited or no significant mediation effects.

RESULTS & DISCUSSION

The instrument used in this research demonstrated strong internal consistency (Cronbach's $\alpha > 0.75$), indicating that the survey scales reliably measured the intended constructs. Generational patterns in traditional asset ownership were examined to test Hypothesis 1. Results from chi-square tests revealed statistically significant differences across generational cohorts in terms of gold and real estate holdings ($p < .001$). A high proportion of the Silent Generation and Baby Boomer respondents reported ownership of gold (approximately 90–96%), whereas ownership among Millennials and Gen Z was substantially lower, at 41% and 35% respectively. Similar generational differences were observed in real estate ownership, with around 95% of Boomers holding property compared to just 40–54% of younger cohorts.

These findings suggest a declining reliance on traditional physical wealth among younger generations, potentially due to shifts in socio-economic context, modernization, and greater urban exposure. In older Indian households, assets like gold and property have historically been seen as stable stores of value and indicators of status. Khandelwal (2025) noted that gold purchases remain concentrated among less educated, lower-income households—demographics typically aligned with older generations. Meanwhile, recent trends forecast that younger Indians, particularly Millennials and Gen Z, are increasingly becoming first-time home buyers by 2030, indicating a growing inclination toward financialized or mixed asset portfolios (Khandelwal, 2025). Thus, although traditional wealth forms remain culturally significant for older groups, this research indicates a generational shift in asset preference, likely driven by modernization and digital financial access.

Hypothesis 2 investigated the effect of Indigenous Wealth Preservation Motivation (IWPM) on investment behavior. Multiple regression analysis showed that IWPM significantly predicted contemporary investment behavior ($\beta = .400$, $p < .001$), while the actual percentage of traditional assets held was not a significant predictor ($\beta \approx .03$, n.s.). This implies that the internalized motivation to preserve traditional wealth may foster proactive financial behavior, regardless of the amount of such wealth held. A possible interpretation is that individuals motivated by cultural or familial responsibility toward asset preservation also show greater engagement in investment activities to ensure continuity or growth of wealth.

The findings align with broader literature. For instance, Antwi and Naanwaab (2022) observed that in the United States, Baby Boomers exhibited stronger investment participation, suggesting that cultural or generational norms may enhance financial engagement. In this research, investment behavior was also significantly associated with higher levels of education ($\beta = .568$) and income ($\beta = .224$), reaffirming the established role of financial literacy and socio-economic status as enablers of investment. Gender was a significant factor ($\beta \approx .086$, $p < .05$), with male respondents showing higher investment activity—supporting prior findings that men are generally more risk-assuming and often dominate household financial decisions (Banerjee et al., 2022). Importantly, age ceased to be a significant predictor when these factors were controlled, suggesting that generational differences in investment behavior are mediated by digital adoption, education, and cultural beliefs, rather than age per se.

The third hypothesis related to financial risk attitudes. The analysis revealed that IWPM was significantly associated with lower risk aversion ($\beta = .355$, $p < .001$), indicating higher risk tolerance. Again, the proportion of wealth held in traditional assets was not a significant predictor. Although traditional values are often assumed to correlate with caution or risk-avoidance, this research suggests otherwise. Motivated traditionalists may feel a sense of stewardship that encourages wealth growth through risk-taking, possibly to maintain family status or legacy. This contrasts with findings from high-income contexts; for example, Antwi and Naanwaab (2022) noted that older cohorts in the U.S. were more risk-averse than younger ones.

In the present study, the association between

IWPM and risk tolerance appears to be mediated by both negative and positive pathways. IWPM was negatively correlated with financial literacy ($r = -.358$, $p < .001$) and digital adoption ($r = -.475$, $p < .001$), both of which typically increase risk aversion. Conversely, IWPM was positively associated with cultural influence in financial decisions, which was found to reduce risk aversion. This suggests that cultural norms and beliefs may serve to offset caution typically driven by low literacy or technological inexperience.

The fourth hypothesis tested for indirect effects of generational cohort on investment behaviour and risk aversion through multiple mediators. For investment behaviour, the analysis identified significant mediation effects via financial literacy and digital adoption. IWPM was associated with lower financial literacy and digital adoption, both of which, in turn, reduced investment behaviour. These findings support the literature emphasizing that motivation alone does not translate into action without access and knowledge (Lusardi & Mitchell, 2014). Other factors such as financial attitude, household decision-making, and cultural influence did not significantly mediate the IWPM–IB relationship.

For risk aversion, mediation was observed through financial literacy and cultural influence. IWPM reduced financial literacy—resulting in increased risk aversion—while simultaneously increasing cultural influence, which lowered risk aversion. The net effect was a reduction in overall risk aversion. These dual pathways reveal the complex interaction between formal and informal influences on financial decision-making. Generational cohort effects on risk aversion were also mediated by these variables, with older participants demonstrating lower digital and financial literacy but higher cultural influence, ultimately explaining their differing risk profiles.

In a nutshell, this research noted clear generational differences in traditional wealth ownership, with younger cohorts increasingly favouring financial or hybrid assets over gold and real estate. Despite this shift, Indigenous Wealth Preservation Motivation remains a strong predictor of financial behaviour and risk-taking across all age groups. Notably, cultural orientation appears to enhance, rather than hinder, financial modernization. Although tradition-oriented individuals often face lower financial literacy and digital exposure, their cultural norms may foster more engaged and risk-tolerant investment behaviour. These insights align with existing literature on financial literacy, gender, and cultural effects (Banerjee et al., 2022; Lusardi & Mitchell, 2014), while contributing new perspectives on the integration of indigenous values in modern financial ecosystems. Ultimately, tradition—when supported by education and access can act as a powerful enabler of inclusive financial growth in India.

LIMITATIONS OF THE STUDY

The following are some potential limitations of this research:

1. Snowball Sampling has been used in this study. Non-random selection limits generalizability to the broader Indian population and may introduce selection bias.

2. There could be issues related to the Self-reported data. Reliance solely on questionnaires introduces potential social desirability bias and common method variance without external validation.

3. Due to vast scope of research and limited resource availability, only limited exploration of mediating variables could be done.

CONCLUDING OBSERVATIONS

This research explains how different generations of Indians view traditional wealth like gold and property, and the results reveal some surprising changes happening in Indian families today. The study observed that older people (Silent Generation and Baby Boomers) still strongly prefer traditional assets—around 90-96% of them own gold and 95% own property. But younger Indians (Millennials and Gen Z) are moving away from these traditional forms, with only 35-41% owning gold and 40-54% owning property.

However, the most interesting finding is that this shift does not mean younger Indians have given up on family wealth values. The research documents that people's motivation to preserve family wealth—what the study calls Indigenous Wealth Preservation Motivation (IWPM)—is still very strong across all age groups. This motivation strongly influences how people invest money and take financial risks, regardless of whether they actually own gold or property. This implies that younger Indians haven't rejected the idea of protecting family wealth; they've simply found new ways to do it. Instead of buying gold and property like their parents, they're investing in stocks, mutual funds, and other modern financial options. They understand that the main goal of keeping the family financially secure for future generations can be achieved through different types of investments.

The study also revealed something unexpected: people who care more about preserving traditional wealth are actually more willing to assume financial risks, not less. This goes against what many people assume about traditional values making people overly careful with money. It seems that when people feel responsible for maintaining their family's wealth, they are more likely to take smart risks to grow that wealth. The research shows that cultural beliefs play a big role in how people make financial decisions. Even when people have less knowledge about modern finance or technology, their cultural background can still push them to be more active investors. This creates an interesting balance where different generations bring different strengths—older people have cultural wisdom while younger people have technical knowledge.

These findings are important for understanding India's financial future. They suggest that Indian society is not experiencing a break from tradition but rather a smart blending of old wisdom with new opportunities. As younger Indians start buying homes and building wealth in the coming years, they're likely to create mixed portfolios that respect family values while taking advantage of modern financial tools. The research also found that education and income are still very important for investment behaviour, and men tend to invest more than women. But age itself doesn't matter as much once education, technology use, and cultural beliefs are adequately accounted for.

Future researchers can build on this work by studying how these patterns differ across different regions of India, comparing urban and rural areas, and tracking how these wealth beliefs change over time. They could also explore how banks and financial companies can better serve families going through this transition. For practical use, these findings help financial advisors, government officials, and banks understand that traditional family values can actually encourage modern investing. This knowledge can help create better financial products and services that work for both older and younger Indians, supporting the country's overall financial growth.

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Sentiment-Driven Market Dynamics: Evidence from Google Trends and Indian Stock Indices

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ABSTRACT

This study investigates the intersection of digital behavior and financial market activity by employing Google Trends data as a non-traditional, data-driven indicator of investor sentiment in the Indian context. Recognizing that investor psychology often drives market prices beyond fundamental values, the research explores whether web search query data can effectively capture and reflect investor sentiment and its influence on Nifty 50 index returns. Using the Google Sentiment Index (GSI) as a proxy for investor mood, the study employs quantile regression and Vector Autoregression (VAR) models to analyze the dynamic relationship between sentiment and market performance across varying return distributions. The quantile regression results indicate that the relationship between GSI and Nifty returns is asymmetric and non-linear with a significant negative effect during bearish conditions and a positive effect during bullish phases. This pattern highlights that sentiment exerts stronger short-term influence in extreme market conditions. The VAR analysis indicates a bidirectional feedback relationship between sentiment and returns; however, the predictive power of returns on sentiment is more pronounced, suggesting that investor sentiment is largely reactive to past market performance rather than predictive of future movements. Variance decomposition further confirms that daily market fluctuations are primarily self-driven, with sentiment playing a minimal role in explaining short-term return variance. The findings underscore that while sentiment derived from online behavior offers valuable behavioral insights, it serves as a weak predictor of daily returns and is more useful for identifying broader market trends and risk dynamics. By integrating behavioral finance with big data analytics, this research demonstrates the potential of Google search activity as a real-time tool for monitoring investor psychology, enhancing risk management, and informing strategic investment decisions in the Indian financial markets.

KEYWORDS

Behavioral Finance, Google Trends, Google Sentiment Index (GSI), Indian Stock Market, Investor Sentiment, Quantile Regression, Vector Autoregression (VAR)

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INTRODUCTION

In the evolving landscape of financial research, there has been a growing recognition of the limitations of traditional economic theories in explaining real-world market behavior. Classical finance models often assume that investors are fully rational and that markets are efficient. However, numerous instances of market overreactions, bubbles and crashes have challenged these assumptions, paving the way for the rise of behavioral finance as a complementary framework (Barberis & Thaler, 2003). Behavioral finance posits that psychological factors and cognitive biases significantly influence investor decisions, often leading to irrational market outcomes.

One such behavioral factor that has received increasing attention is investor sentiment, the overall attitude of investors toward a particular market or asset. Investor sentiment can be driven by various elements, including media coverage, economic news and social signals. This sentiment, especially when aggregated, have the potential to influence market prices, trading volumes, and volatility, even in the absence of fundamental information (Baker & Wurgler, 2007). While investor sentiment has long been considered an abstract concept, the digital age has introduced innovative methods to quantify and analyze it more objectively.

Among these new tools, Google trends has emerged as a powerful proxy for capturing public interest and investor attention. The Search Volume Index (SVI) provided by Google aggregates the frequency of specific search terms over time, reflecting what people are thinking about or concerned with at any given moment. Da, Engelberg, and Gao (2011) demonstrated that increased search activity on financial terms was associated with higher trading volumes and temporary stock price movements in the U.S. market. Similarly, Preis, Moat, and Stanley (2013) observed that search query volumes could serve as leading indicators of financial market trends.

Building on this growing body of literature in the context of the Indian stock market, the current study aims to examine the degree to which search query data obtained through Google trends can be utilized as a direct proxy for investor mood. The surge in digital engagement over years is also mirrored in the behavior of retail investors, who increasingly turn to search engines to gather market information, understand financial instruments and make investment decisions (Kumar & Garg, 2019). Understanding whether this online search behavior can effectively reflect market sentiment and, in turn, predict or explain stock market returns is crucial for multiple stakeholders. For investors, it offers a new dimension of sentiment analysis that can enhance trading strategies. For policymakers and regulators, it provides insights into market psychology and the potential risks of herd behavior. For researchers, it opens avenues for integrating big data tools with behavioral and empirical finance (Tetlock, 2007).

This study, therefore, aims to evaluate whether Google search volumes related to financial keywords are significantly associated with the performance of Indian stock indices. By combining behavioral finance concepts with data-driven methods, this research contributes to both theory and practice, highlighting how digital traces of investor attention can help bridge the gap between psychology and market behavior in an emerging economy.

LITERATURE REVIEW

Recent developments in financial research have underscored the limitations of traditional economic theories in explaining actual market behavior. Classical finance models often assume fully rational investors and efficient markets. Traditional finance, grounded in the principles of rational behavior and efficient markets, has served as the foundation of financial theory for decades. Markowitz's (1952) Modern Portfolio Theory introduced key concepts like diversification and the efficient frontier, shaping how portfolios are constructed. This was further developed by

Sharpe (1964) and Lintner (1965) through the Capital Asset Pricing Model (CAPM), which links expected returns to systematic risk. Fama's (1970) Efficient Market Hypothesis (EMH) built on these ideas, arguing that asset prices fully reflect all available information, making it difficult for investors to consistently outperform the market. Together, these theories formed the core of traditional finance, emphasizing rational decision-making and market efficiency, and provided a mathematical framework for understanding asset pricing, risk and investor behavior.

However, the inability of traditional models to explain certain market anomalies and investor behaviors led to the rise of behavioral finance. Influenced by the psychological research of Kahneman and Tversky (1979), this field integrates cognitive and emotional factors into financial decision-making. Behavioral finance highlights how biases, heuristics, and social influences can cause deviations from rationality, offering insights into phenomena that classical theories often fail to account for.

Investor sentiment, defined as beliefs not fully supported by fundamentals (Baker & Wurgler, 2007), plays a key role in behavioral finance. Unlike traditional finance, sentiment-based research explains anomalies in asset pricing and investor actions, especially for speculative stocks (Baker & Wurgler, 2006). Various sentiment measures surveys, market indicators like the VIX (Bandopadhyaya & Jones, 2008), media tone (Tetlock, 2007), and digital data from social media and Google Trends (Bollen et al., 2011; Li et al., 2014) have evolved, with recent approaches integrating machine learning for improved prediction (Ren et al., 2019). However, the absence of a universal sentiment metric and disagreement over its structure (Raissi & Missaoui, 2015; P.H. & Rishad, 2020) remain key challenges. Despite these limitations, sentiment analysis enriches financial modeling and market forecasting by offering a nuanced perspective beyond rational behavior assumptions.

More recently, the emergence of big data and advanced analytics has transformed financial research. Tools like Google Trends, which track search query volumes, have become powerful indicators of public interest and sentiment. These web-based data sources offer timely, real-world insights especially useful when traditional datasets are slow, noisy, or incomplete. In finance, they enable new methods of assessing investor attention, forecasting market movements, and understanding how information spreads across markets.

Behavioral finance research further strengthens the role of investor sentiment as a core state variable that complements and challenges traditional asset-pricing frameworks. Recent systematic reviews show that sentiment is central for explaining short-run return–sentiment linkages, particularly around crises and in emerging and frontier markets where information frictions are pronounced (Prasad et al., 2022; Luong et al., 2024; Kamath et al., 2024). These studies highlight that assumptions of fully rational investors and efficient markets cannot easily reconcile the observed short-horizon predictability and asymmetric return responses to optimistic versus pessimistic sentiment, reinforcing the limitations of traditional models already noted in earlier behavioral and sentiment-based work (Kamath et al., 2024; Beckmann et al., 2024).

In parallel, sentiment measurement up to 2024 has broadened from survey- and price-based indicators to more data-driven approaches, but still lacks a universal benchmark. Systematic review evidence documents substantial heterogeneity in how sentiment indices are constructed, including differences in data sources, weighting schemes and aggregation rules, which often produce divergent signals even for similar markets and horizons (Prasad et al., 2022). At the same time, new studies employing sentiment analysis and deep learning on news and social-media text report improvements in stock-return forecasting, while also revealing strong model- and context-dependence in the extracted sentiment measures (Akyüz et al., 2024; Hajek et al., 2025). Despite methodological advances, there is still no consensus on a single, universally accepted sentiment index, and disagreement over the dimensionality and structure of sentiment remains a central challenge for sentiment-based asset-pricing research (Prasad et al., 2022).

Research on the influence of google trends on stock performance in India has made significant strides, yet several gaps remain that could be addressed to enhance understanding of this relationship While existing studies have established a positive correlation between Google search volumes and stock indices, the underlying mechanisms causing this association are still not fully understood. Most research has focused primarily on descriptive statistics and correlation analyses without delving deeply into the specific contexts that might amplify these effects (Bijl et al., 2024). The current literature predominantly focuses on weekly data for long term trends due to ease in availability of the weekly data. By focusing on daily data, researchers can better assess the real-time impact of investor attention on stock prices, leading to more timely and informed trading decisions. Moreover, daily data allows for a more granular analysis of short-term market dynamics. By utilizing daily Google trends data alongside historical stock performance metrics, the present study can develop more robust models that account for immediate shifts in investor sentiment. And present study aims to contribute to the behavioral finance literature by validating the use of digital data sources specifically web search behavior as quantifiable metrics for understanding and forecasting investor sentiment in emerging markets.

RESEARCH METHODOLOGY

Purpose of the Study

By focusing on India's most widely tracked stock index NSE Nifty 50, this study provides insight into how retail and institutional investor behavior, reflected in search engine activity, may correspond with shifts in market performance. The primary objective of this study is to examine the relationship between web search query data measured by the Google Sentiment Index (GSI) and stock market returns of NSE Nifty.

Specifically, this study seeks to assess whether fluctuations in the frequency of Google search queries related to financial terms and market events can serve as a reliable and real-time proxy for investor sentiment, and whether such sentiment affects index fluctuations in a quantifiable way.

Research Design

This exploratory study investigates the correlation between web search-based query data as a direct proxy for investor sentiment and its impact on predicting returns in the Indian stock market. The study aims to determine whether web search-based query data, as measured by the Google Sentiment Index (GSI), can serve as a direct proxy for investor sentiment concerning Indian stock market returns.

The data is collected from secondary sources for financial time series and keywords identified as investor's sentiment proxy. The financial data for stock market returns and sectoral returns is collected from the NSE and BSE website. The data regarding the keywords identified for Google search is collected from the Google trends website and Trendecon R package.

Google Trends, launched in 2012 (evolving from Google Insights for Search introduced in 2008), is a data analytics service that provides normalized, relative search volume indices (0–100) for specific keywords across different regions, languages, categories, and search channels, allowing researchers to infer public attention and investor sentiment levels. The platform provides weekly data for up to five years, and monthly data for longer periods. Risteski and Davcev (2014) proposed a method to merge weekly and monthly series, but Volyublennaia (2014) noted that this approach did not yield reproducible results, recommending separate evaluation of five-year periods. Later, Eichenauer et al. (2020) developed the trendecon R package, which harmonizes multiple Google Trends queries (daily, weekly, and monthly) to generate stable, consistent, and long-term daily economic indices. The package ensures robustness by repeated querying and alignment of frequencies, preserving long-term trends and enabling the creation of real-time macroeconomic indicators such as confidence and activity indices. Thus, in this study, data are sourced using the trendecon R package to ensure stability and consistency across frequencies, addressing the normalization issues inherent in Google Trends data.

Financial keywords were selected using prior literature, Google Trends suggestions, and financial dictionaries such as Harvard IV-4 and Lasswell of the General Inquirer. Low-value terms were dropped. Following Preis et al. (2013) and Vosen & Schmidt (2011), correlation analysis was applied to retain terms strongly associated with market movements. Following the approaches of Brochado (2020) and Jung and Seo (2025), the final sentiment index in the present study is constructed by aggregating the shortlisted high-correlation keywords to capture investor attention.

$$GSI_t = \frac{1}{n}\sum_{i=1}^{n} SV_{i,t} \quad (1)$$

Where, GSIt represents the Google Sentiment Index at time t. SVi, t stands for the Search Volume for the ith keyword at time t. It indicates how frequently a specific term related to investor sentiment is searched on Google during time t, n is the total number of keywords used to construct the sentiment index.

The final GSI included keywords are, “Nifty 50”, “ Stocks”, “Sensex Today”, “Nifty 50 Today”, “Sensex Share Price”, “Bombay Stock Exchange”, “Nifty 50”, “Sensex”, “Sensex Share Price Today”, “Sensex Live Today”, “ Sensex Today India”.

The studied time span is of 14 years beginning from 1st January 2010 till 31st December 2023 with daily frequency. Initially for keyword collection R software is used and further for statistical analysis E- Views is used to analyze the impact of investor sentiment proxied by Google Sentiment Index on different quantiles of stock market returns by using Quantile Regression. While traditional linear regression models (like OLS) estimate the average effect of independent variables on the dependent variable, quantile regression enables the investigation of how the impact of investor sentiment varies across different points (quantiles) of the return distribution, such as during market booms (upper quantiles) or downturns (lower quantiles). This is particularly important in financial markets, where sentiment-driven behavior may have asymmetric effects—stronger during extreme market conditions. By applying quantile regression, this study aims to uncover whether Google search activity has a differential impact on stock returns in bullish, bearish, and neutral phases of the market. This approach provides a more comprehensive understanding of the sentiment-return relationship than mean-based models. To evaluate the lead lag relationship, Vector Autoregression (VAR), the causality method is applied individually between GSI and Indian stock market indices. The VAR analysis examine the impact of the previous lags of the GSI and stock indices market returns assumed as each of the series as endogenous variable in VAR system.

Data Analysis and Intrepretation

The relationship between Google Sentiment Index (GSI) indicating the web search query data in Google as a measure of investor’s sentiment and the stock index returns using NSE Nifty as index returns in India is determined with the help of descriptive analysis of the included time series variables (GSI, Nifty index, and Nifty returns). The unit root test is used to examine the nature of stationarity in each included time series. The correlation and regression analysis are applied for examining the linear relationship between the GSI and stock index returns. The quantile regression analysis is applied to find out the relationship between the quantile's movements within the series and finally the VAR methodology is used to examine the nature of causality between the GSI and stock index returns.

Table 1: Linear Regression - Dependent Variable: Nifty Return

	Daily data		
Independent Variable	Coefficient	SE	T Stats
GSI	-0.0003	0.0009	-4.120**
Intercept	0.002	0.0004	5.162**
F stats	16.975 (0.000)		
R Square	0.003		

*(Note: Table reports coefficients and t-values, where *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively) (Source: Self, Eviews generated)*

Table 2: Quantile Process Estimates Nifty Returns

Quantile Process Estimates Nifty Returns (Daily)					
	Quantile	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Google Sentiment Index	0.100	-0.00016	0.00002	-9.761	0.000
	0.200	-0.00009	0.00002	-5.358	0.000
	0.300	-0.00005	0.00001	-4.258	0.000
	0.400	-0.00004	0.00001	-3.812	0.000
	0.500	-0.00001	0.00001	-0.873	0.382
	0.600	0.00001	0.00001	1.181	0.237
	0.700	0.00003	0.00001	2.819	0.004
	0.800	0.00004	0.00001	3.044	0.002
	0.900	0.00007	0.00002	3.450	0.000
Constant	0.100	-0.0048	0.0006	-7.80	0.000
	0.200	-0.0028	0.0007	-4.020	0.000
	0.300	-0.0014	0.0004	-2.868	0.004
	0.400	0.0002	0.0004	0.698	0.484
	0.500	0.0010	0.0004	2.554	0.010
	0.600	0.0021	0.0004	4.479	0.000
	0.700	0.0037	0.0005	7.299	0.000
	0.800	0.0061	0.0005	11.076	0.000
	0.900	0.0088	0.0008	10.572	0.000

(Source: Self, Eviews generated)

The table presents the results of linear regression models to assess the relationship between GSI and Nifty return. The coefficient for GSI is statistically significant (p-value < 0.001), indicating a strong relationship between GSI and Nifty Return. The negative coefficient for GSI suggests an inverse relationship. This implies that as GSI increases, Nifty return tends to decrease, and vice versa.

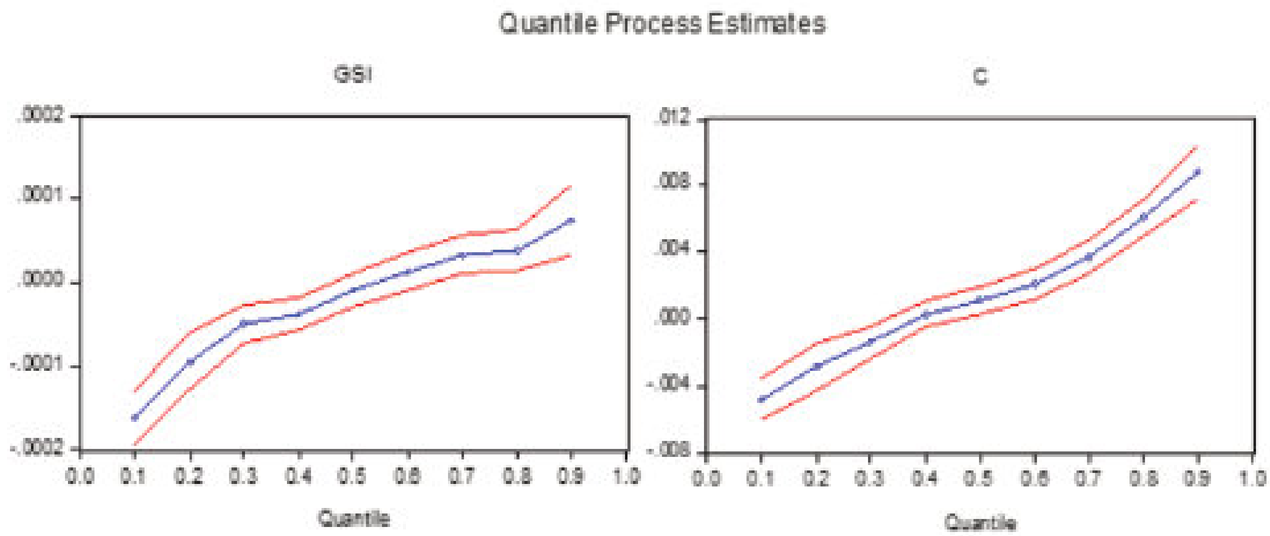
The linear regression provides the conditional mean of stock indices return using average values of GSI. However, the one of the major drawbacks of linear regression is the assumption of linear relationship and the possibility to ignore the multiple modes in stock indices returns. In such case the quantile regression is proved more effective as it can explain the stock indices behaviour at different percentiles due to the changes in different percentiles in GSI.

Quartile regression between Nifty and GSI

The estimated coefficients and quantile graph is reported in Table 2 and Figure 1.

The quantile regression results reveal that the impact of the Google Sentiment Index (GSI) on Nifty 50 returns varies across different points of the return distribution. At lower quantiles (0.10 to 0.50), the coefficients are negative and statistically significant, indicating that increased sentiment correlates with decreased returns during less favorable market conditions. This suggests that in bearish markets, heightened sentiment might coincide with lower returns indicating positive sentiment might lead to overvaluation and a subsequent correction. In the middle quantiles (0.50 to 0.60), the coefficients are not statistically significant, implying a weaker or negligible relationship between sentiment and returns. Conversely, at higher quantiles (0.60 to 0.90), the coefficients become positive and significant, showing that during bullish market conditions, higher sentiment corresponds to increased returns. Positive sentiment seems to coincide with higher Nifty returns during periods of strong performance (higher quantiles), indicating that positive sentiment may amplify gains in favorable market conditions. Overall, the analysis highlights that the influence of market sentiment on returns is not uniform but varies, becoming more positive as market performance improves.

Figure 1: Quantile Process Estimates Nifty Returns (Daily Data)



(Source: Self, Eviews generated)

The graph suggests that the effect of GSI on Nifty 50 returns varies across return levels, being more positive at higher quantiles, while the effect of constant is generally stable with slight increases at higher quantiles. This further supports the earlier finding that sentiment, as captured by GSI, may play a stronger role during periods of higher returns.

Quantile Slope Equality Test and Symmetric Quantiles Test

The results of Quantile Slope Equality Test and Symmetric Quantiles Test is reported in table no 3. The result reported that the slope of the quantile is not equal at the different quantiles, however maintains the symmetry at 25th and 75th quantiles. As a result, it can be said that the quantile regression approach is a more effective way to analyse the nonlinear relationship between the returns of the Nifty index and the GSI.

Table 3: Quantile Slope Equality Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test	39.84742	2	0.0000	
Restriction Detail: b(tau_h) - b(tau_k) = 0				
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**
0.25, 0.5	Google Trend	-0.00006	0.00001	0.0000
0.5, 0.75		-0.00004	0.00001	0.0000

(Source: Author's Own, Eviews generated)

Table 4: Symmetric Quantiles Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	
Wald Test	1.584488	2	0.4528	
Restriction Detail: b(tau_h) + b(1-tau) - 2*b(.5) = 0				
Quantiles	**Variable**	**Restr. Value**	**Std. Error**	**Prob.**
0.25, 0.75	Google Trend	0.0000	0.0000	0.3820
0.5, 0.75	C	0.0008	0.0007	0.2631

(Source: Author's Own, Eviews generated)

Table 5: VAR Granger Causality/Block Exogeneity Wald Tests Nifty Return

Dependent variable: NIFTY Returns (Daily Data)			
Excluded	**Chi-square**	**Degree of freedom**	**Prob.**
GSI	14.302	7	0.0461
All	14.302	7	0.0461
Dependent variable: GSI			
Excluded	**Chi-square**	**Degree of freedom**	**Prob.**
NIFTY return	61.028	7	0.0000
All	61.028	7	0.0000

(Source: Author's Own, Eviews generated)

The Symmetric Quantiles Test indicates that there is no significant evidence to suggest that the distribution of the data is asymmetric around the median for the given time period (weekly). The test results support the hypothesis of symmetry, implying that the data is balanced on both sides of the central tendency.

Causality between Stock Indices (Nifty and GSI)

The VAR methodology begins with selection of the optimum lag length of the included GSI series and Nifty indices returns series. The lag length is selected using different lag length criteria (SC, AIC and HQ). The results of lag length selection criteria for incorporating the lags of the GSI series and Nifty indices returns series are contained in Table 5.

The results from the Granger causality tests reveal significant insights into the dynamic relationship between investor sentiment proxied by GSI and Nifty stock market returns. Where Nifty returns serve as the dependent variable shows a Chi-square value of 14.302 with 7 degrees of freedom and a corresponding p-value of 0.0461. Since this p-value is less than the 5% significance threshold, the null hypothesis that GSI does not Granger-cause NIFTY returns is rejected. This indicates that daily fluctuations in Google search interest significantly help predict Nifty market movements, suggesting that investor sentiment reflected in search behavior carries meaningful information for short-term return dynamics. Conversely, when GSI is taken as the dependent variable, the Chi-square statistic is 61.028 with a p-value of 0.0000, which is highly significant (Table 6). This result implies that daily market returns also Granger-cause changes in GSI, pointing to a bidirectional causal relationship. Thus, there exists a feedback loop on a daily basis where both investor sentiment and market returns influence each other.

Table 6: Variance Decomposition Function of Nifty Return & Google Trends

Variance Decomposition of Nifty returns Daily Data				Variance Decomposition of GSI Daily Data		
Period	**S.E.**	**Nifty return**	**GSI**	**S.E.**	**Nifty return**	**GSI**
1	0.0100	100.00	0.00	5.585	2.08	97.91
2	0.0104	99.91	0.08	6.037	2.62	97.37
3	0.0106	99.90	0.09	6.049	2.94	97.05
4	0.0106	99.88	0.11	6.073	3.23	96.76
5	0.0106	99.88	0.15	6.100	3.80	96.19
6	0.0106	99.87	0.12	6.127	4.27	95.72
7	0.0106	99.86	0.13	6.167	4.67	95.32
8	0.0106	99.86	0.13	7.141	4.19	95.80
9	0.0106	99.83	0.16	7.578	4.25	95.74
10	0.0106	99.83	0.164	7.624	4.45	95.54

(Source: Author's Own, Eviews generated)

The results depicts that the Nifty returns Indian stock market is explained by 99.835% with the help of its own lagged behaviour and only 0.164 % due to the GSI behaviour. However, in Table no. 6 the variance decomposition of GSI, the results reported the variance of GSI explained by 95.54% with the help of its own lagged behaviour and only 4.45 % due to the previous lags of Nifty returns. The strong self-explanatory nature of Nifty returns (99.8% at period 10) suggests that market movements are predominantly influenced by past market performance rather than sentiment. The increasing explanatory power of Nifty returns on GSI (from 2.08% in period 1 to 4.45% in period 10) highlights the significant role of past market performance in shaping sentiment over time.

DISCUSSION

The purpose of this research is to explore the intersection of digital behavior and financial market activity by utilizing Google trends data as a non-traditional, data-driven indicator of investor psychology in the Indian context. As investor sentiment plays a vital role in market dynamics often driving prices beyond what fundamentals would suggest capturing it through real-time online behavior offers a novel and practical approach to understanding market fluctuations.

Through the objective of examining the relationship of web search query data as a direct proxy or direct reflector for investor's sentiment with Nifty index returns in India, the study seeks to determine the extent to which web search trends reflect investor sentiment and influence the performance of Nifty returns in the Indian financial markets. This analysis highlights that the effect of sentiment on returns varies across the return distribution, with more pronounced effects in extreme market conditions. The results of a quantile regression analysis examining the relationship between Nifty 50 returns (dependent variable) and the Google Sentiment Index (independent variable) indicates that the relationship between index returns and the Google Sentiment Index (GSI) varies across different points in the return distribution. The effect of the GSI on index returns is not uniform. It has a significant negative impact during lower returns and a significant positive impact during higher returns, reflecting how market sentiment influences returns differently across various market conditions. The daily coefficients tend to be more sensitive, showing a stronger immediate relationship between sentiment and returns. Negative coefficients in the lower quantiles and positive in the higher quantiles indicate significant short-term impacts of sentiment.

The results of the Vector Autoregression (VAR) model for daily data suggest a bidirectional relationship between the GSI and index returns, but with differing levels of statistical significance. The findings indicate a feedback relationship between GSI and index returns. However, the stronger significance of index returns in predicting GSI suggests that market movements may have a greater impact on sentiment than sentiment has on market movements. This aligns with the idea that investors react strongly to past market performance when forming sentiment, while sentiment itself, though influential, has a comparatively weaker effect on future returns. This suggests that sentiment is largely influenced by stock returns rather than the other way around, reinforcing the idea that investors' mood depends on how the market has performed recently.

The variance decomposition results highlight the differing roles of investor sentiment (GSI) in explaining index returns across daily timeframe. In the daily data, index returns are almost entirely self-driven, with GSI contributing very minute to the variance by the tenth period. This suggests that short-term market fluctuations are largely independent of sentiment, and other market factors such as macroeconomic news, institutional flows, and technical indicators drive daily returns. Similarly, GSI itself is predominantly influenced by its past values, with index returns explaining only few percentage points of its variance over time. This indicates that while market performance does have some influence on daily sentiment, the effect is relatively weak.

The key takeaway is that daily market movements are primarily driven by internal price dynamics, and sentiment indicators alone are not strong predictors of short-term returns. This suggests that traders and investors considering sentiment-based strategies should focus on longer holding periods rather than intraday movements.

CONCLUDING OBSERVATIONS

The rising prominence of behavioral finance has brought investor sentiment to the forefront as a critical factor influencing stock market dynamics, particularly those anomalies and fluctuations not adequately explained by traditional financial theories. In this evolving landscape, the use of alternative data sources has opened new avenues for understanding market behavior. Among these, Google trends offers a novel, real-time, and publicly accessible proxy for gauging investor attention and sentiment. Google search trends can act as early warning signals for financial instability or systemic risk. This study demonstrates that Google trends derived GSI serves as a viable proxy for investor sentiment in Indian markets, with effects on Nifty 50 returns varying by market regime—stronger in extremes via quantile regression. However, daily dynamics reveal returns primarily drive sentiment (per VAR), not the reverse, and sentiment explains negligible short-term variance. Traders should prioritize longer horizons for sentiment strategies, as daily fluctuations rely more on internal price momentum, macro news, and institutional flows than online search behavior. A sudden surge in queries for terms like "default," "bankruptcy," "stock market crash," or "financial crisis" may indicate rising anxiety among market participants or the public. Risk managers can use such sentiment data to proactively assess vulnerabilities in their portfolios. By recognizing sentiment-driven warning signs early, they can implement defensive strategies such as rebalancing portfolios, increasing hedging positions, or reducing exposure to high-volatility assets. This approach adds a behavioral layer to traditional risk management, allowing for a more dynamic and psychologically informed understanding of market threats. GSI provides actionable insights for both investors and policymakers in navigating Nifty 50 dynamics. Investors benefit from real-time sentiment proxies to time trades in extreme market regimes, integrate into risk models for volatility forecasting, and adopt longer-term strategies given weak daily predictive power. Policymakers like RBI/SEBI can monitor for bubbles/ panics, calibrate interventions during downturns, and use it alongside traditional indicators to enhance market stability and promote fundamentals-driven reforms. Overall, it bridges behavioral data with policy, fostering resilient Indian markets amid sentiment fluctuations. This research will help bridge the gap between traditional financial models and modern behavior-based approaches, demonstrating how publicly available search data can enrich investment analysis, portfolio strategy, and market forecasting in the Indian financial ecosystem.

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Doctoral Abstract

Hybrid Information Theoretic Measures and Their Applications in Data Mining

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The abstract is of the thesis titled "Hybrid Information Theoretic Measures and Their Applications in Data Mining" submitted by Dr. Sonia Saini, who earned her Ph.D. in Statistics in 2022 from Maharshi Dayanand University, Rohtak. The supervisors were Dr. Priti Gupta, Guide, Professor, Department of Statistics, M.D.University, Rohtak, India and Dr. Pratiksha Tiwari, Co-Guide and Associate Professor, Delhi Institute of Advanced Studies, GGSIPU, Delhi, India.

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INTRODUCTION

Information theory, introduced by Shannon (1948), revolutionized the understanding of communication and uncertainty by providing a mathematical measure of information through entropy. Shannon entropy quantifies the average uncertainty associated with a random variable and has been widely applied in communication systems, statistics, pattern recognition, machine learning, and signal processing. Despite its success, Shannon's framework relies on precise probability distributions, which are often unavailable or unreliable in practical situations.

In real-life applications such as medical diagnosis, decision-making, pattern recognition, and data mining, information is frequently imprecise, incomplete, or vague. Human reasoning itself is not binary but involves partial truths and subjective judgments. Classical probabilistic models fail to adequately represent such complexities. To overcome these limitations, non-probabilistic approaches based on fuzzy set theory, rough set theory, soft set theory, and intuitionistic fuzzy set theory were developed.

Fuzzy set theory, introduced by Zadeh in 1965, allows elements to belong to a set with varying degrees of membership. Rough set theory, proposed by Pawlak in 1982, models uncertainty using lower and upper approximations. Soft set theory, introduced by Molodtsov in 1999, provides a parameterized framework for uncertainty representation. Intuitionistic fuzzy sets, developed by Atanassov in 1986, extend fuzzy sets by incorporating degrees of non-membership and hesitation.

This doctoral research integrates information theory with these uncertainty-handling frameworks to develop hybrid information theoretic measures. The primary motivation is to enhance the capability of entropy, similarity, and distance measures in handling complex and uncertain data. The focus is on applications in data mining and decision-making, where effective uncertainty modeling is crucial for accurate analysis and knowledge discovery.

REVIEW OF LITERATURE

The evolution of information theory represents a systematic effort to quantify uncertainty and information content in communication and decision-making systems. Early foundations of information theory can be traced to telecommunication studies by Hartley (1928) and Nyquist (1924, 1928), who examined signal transmission capacity and speed. These works laid the groundwork for the formal development of information theory by Shannon (1948), who introduced entropy as a quantitative measure of uncertainty in probabilistic experiments. Shannon's formulation revolutionized communication theory and subsequently influenced diverse disciplines such as physics, statistics, economics, biology, psychology, and computer science.

Following Shannon's work, probabilistic information measures were extensively generalized and applied. Weaver (1949) broadened the accessibility of Shannon's ideas, while Kullback (1959) introduced divergence measures to quantify differences between probability distributions. Rényi (1961) proposed a parametric generalization of Shannon entropy, allowing flexibility in sensitivity to probability distributions. Further extensions were developed by Havrda and Charvát (1967), Sharma and Taneja (1977), Tsallis (1988), and Pal and Pal (1989), leading to a wide class of generalized entropy measures. These probabilistic measures found successful applications in clustering, pattern recognition, image processing, and statistical inference. However, their reliance on precise probability distributions limited their effectiveness in real-world situations characterized by vagueness and incomplete information.

To address these limitations, Zadeh (1965) introduced fuzzy set theory, which allows partial membership of elements and provides a natural framework for modeling imprecision inherent in human reasoning. Zadeh (1968) further extended information theory by proposing fuzzy entropy, marking the beginning of non-probabilistic information measures. De Luca and Termini (1972) formalized axiomatic conditions for fuzzy entropy, establishing a foundation for subsequent developments. Later contributions by Kaufman (1975), Yager (1979), Kosko (1986), Pal and Pal (1992), and Bhandari and Pal (1993) introduced various fuzzy entropy measures based on distance, exponential forms, and divergence concepts. These measures demonstrated superior performance in applications such as medical diagnosis, pattern recognition, and decision-making.

The scope of uncertainty modeling expanded further with the introduction of rough set theory by Pawlak (1982), which addresses vagueness through lower and upper approximations without requiring additional information such as membership functions or probability distributions. Rough set theory gained prominence in feature selection, knowledge discovery, and data mining. The integration of fuzzy and rough set theories led to fuzzy rough sets, which combine granularity and fuzziness and have been shown to be particularly effective in attribute reduction and classification problems.

Atanassov (1986) proposed intuitionistic fuzzy sets, extending fuzzy sets by incorporating degrees of non-membership and hesitation. This additional parameter enabled more expressive modeling of uncertainty, especially in situations involving incomplete or conflicting information. Researchers such as Szmidt and Kacprzyk (2001), Wang and Xin (2005), and Hung and Yang (2008) developed distance, similarity, and entropy measures for intuitionistic fuzzy sets, further enhancing their applicability in decision-making and pattern recognition.

Soft set theory, introduced by Molodtsov (1999), provide a parameterized framework for uncertainty modeling, particularly useful in decision-making environments. Subsequent developments developments led to fuzzy soft sets and intuitionistic fuzzy soft sets, which integrate fuzziness and intuitionism with parameterization. Researchers including Maji et al. (2001), Majumdar and Samanta (2011), Jiang et al. (2013), and Li (2014) proposed various distance, similarity, and entropy measures within these frameworks, demonstrating applications in decision support systems and data analysis.

To capture higher levels of uncertainty, interval-valued fuzzy soft sets and interval-valued intuitionistic fuzzy soft sets were introduced. These models allow membership and non-membership values to be expressed as intervals, offering greater flexibility and realism. Contributions by Yang et al. (2009), Mukherjee and Sarkar (2014, 2015), Feng et al. (2017), and Sulaiman et al. (2018) advanced distance, similarity, and entropy measures in these settings, with applications in medical diagnosis and multi-criteria decision-making.

Despite the extensive literature on individual uncertainty models, existing studies reveal a research gap in the systematic development of hybrid information theoretic measures that unify fuzzy, rough, soft, intuitionistic, and interval-valued frameworks within a consistent information-theoretic perspective. Moreover, comparative studies highlighting the effectiveness of such hybrid measures in data mining tasks—such as feature selection, data reduction, and classification—remain limited. The present research addresses this gap by proposing novel hybrid entropy, distance, and similarity measures and demonstrating their applicability in data mining and decision-making under complex uncertainty environments.

OBJECTIVES OF THE STUDY

The primary objectives of the present doctoral research are:

1. To develop novel non-probabilistic and hybrid entropy measures for various uncertainty models.

2. To propose new distance and similarity

measures for fuzzy, intuitionistic, soft, and rough set-based structures.

3. To verify the theoretical validity and mathematical properties of the proposed measures.

4. To apply the developed measures to data mining tasks such as feature selection and data reduction.

5. To demonstrate applicability in decision-making and medical diagnosis problems.

6. To compare the proposed measures with existing methods and evaluate their effectiveness.

Proposed Measures

1. **Trigonometric Entropy for Fuzzy Rough Set (FRS) and their Application in Medical Area**

Some trigonometric information entropies have been proposed for FRSs and fuzzy rough values, and their validity is also proved. Corresponding to proposed trigonometric entropies, the weighted trigonometric entropies have been proposed for fuzzy rough sets.

Let A be FRS in $\Psi = \{\varphi_1, \varphi_2, \dots \dots, \varphi_n\}$, where $A = \sum_{i=1}^{n} \left[\langle \underline{\varphi_i}, \underline{\varphi_i} \rangle\right] / \varphi_i \; x_i \in \Psi$,

$$E_{sin}(A) = \frac{1}{n}\sum_{i=1}^{n} e_{A;\, sin}(\varphi_i)$$

$$= \frac{1}{n}\sum_{i=1}^{n} sin\; sin \left[\frac{\pi}{2}\left(1 - \frac{1}{2}\left(\left|2\underline{\varphi_i} - 1\right| + \left|2\underline{\varphi_i} - 1\right|\right)\right)\right], \forall \varphi_i \in \Psi, where\ A \in \Gamma^R(\Psi); \varphi_i = \langle \underline{\varphi_i}, \underline{\varphi_i} \rangle$$

$$E_{cos}(A) = \frac{1}{n}\sum_{i=1}^{n} e_{A;\, cos}(\varphi_i)$$

$$= \frac{1}{n}\sum_{i=1}^{n} cos\; cos \left[\frac{\pi}{4}\left(\left(\left|2\underline{\varphi_i} - 1\right| + \left|2\underline{\varphi_i} - 1\right|\right)\right)\right], \forall \varphi_i \in \Psi, where\ A \in \Gamma^R(\Psi); \varphi_i = \langle \underline{\varphi_i}, \underline{\varphi_i} \rangle$$

$$E_{tan}(A) = \frac{1}{n}\sum_{i=1}^{n} e_{A;\, tan}(\varphi_i)$$

$$= \frac{1}{n}\sum_{i=1}^{n} tan\; tan \left[\frac{\pi}{4}\left(1 - \frac{1}{2}\left(\left|2\underline{\varphi_i} - 1\right| + \left|2\underline{\varphi_i} - 1\right|\right)\right)\right], \forall \varphi_i \in \Psi, where\ A \in \Gamma^R(\Psi); \varphi_i = \langle \underline{\varphi_i}, \underline{\varphi_i} \rangle$$

then corresponding to equation (2.3.1), (2.3.2) and (2.3.3). Novel entropies are given below

The proposed framework integrates concepts from fuzzy sets and rough sets to better capture uncertainty and imprecision present in real-world datasets. By combining these paradigms, the measures aim to provide a more reliable representation of incomplete and vague information. The theoretical foundation of these measures is established through axiomatic

It is obvious that proposed entropies lie in the interval [0,1]. Larger the value of entropies the more is uncertainty in A.

After that an application of proposed measures is also discussed which are related to medical diagnosis and data reduction is also done in fuzzy rough environment.

Fuzzy rough set theory offers the flexibility to deal with two types of uncertainty present in information related to decision making or data related problems in daily life. It incorporates fuzzy set theory which considers vagueness within the rough set framework handling uncertain information. A variety of measures and methods for this integration have been proposed in the literature. In this thesis some trigonometric entropies were proposed for fuzzy rough environment and their validity is also proved. Finally, an application of these proposed measures has been used in medical diagnosis and data reduction problems. This shows the significance of proposed measures. These proposed measures can be used in other real-life problems for fuzzy rough environment.

2. **Novel Distance Similarity and Entropy measures for intuitionistic fuzzy set (IFS)**

Some new distance measures for IFSs are derived. Based on these distance measures, similarity measures are also derived for intuitionistic fuzzy sets. Distance and similarity measures are used to compare the differentiation and similarity respectively between two sets, two patterns, two images and two decisions etc. For comparing two intuitionistic fuzzy sets distance and similarity measures are studied by Szmidt and Kacprzyk

(2018), Luo (2018), Cheng et al. (2019).

Maximin distance measure

$$D_1(\Gamma,\Pi),(I,\Lambda)=\frac{1}{3}\left\{Min_j\left(\begin{array}{c}|\Gamma\varphi_j-I\varphi_j|+\\|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|\end{array}\right)\right\}$$

Average distance measure

$$D_2(\Gamma,\Pi),(I,\Lambda)=\frac{1}{6n}\left\{\begin{array}{c}\sum_{j=1}^{n}(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|)\\+Max_j\{(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|+)\}\end{array}\right\}$$

Convex distance measure

$$D_3(\Gamma,\Pi),(I,\Lambda)=\frac{1}{3}\left\{\alpha Max_j(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|)+(1-\alpha)\left\{Min_j\left(\left(\begin{array}{c}|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+\\+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|\end{array}\right)\right)\right\}\right\}$$

Similarity measures for IFS

Distance and similarity are dual to each other. Larger the distance is smaller the similarity between any two sets. This concept is used to define below some similarity measures based on above defined distance measures. Among similarity measures proposed by other researchers, some of those, however, did not satisfy the axioms of similarity or provide counterintuitive cases or are produced in complex way. To overcome this drawback some new similarity measures are derived. The proposed similarity measure depends on the tuples (membership degree, non-membership degree, and dubious factor). Szmidt E, Kacprzyk J (2004), Ye (2011), Shi and Ye (2013), Tian (2013), Rajarajeswari and Uma (2013), Papakostas et al., (2013), have done lot of work in the field of similarity measure of IFS.

Maximin similarity measure:

$$S_1(\Gamma,\Pi),(I,\Lambda)=1-\frac{1}{3}\left\{Min_j\left(\begin{array}{c}|\Gamma\varphi_j-I\varphi_j|+\\|\Gamma^*\varphi_j-I^*\varphi_j|\\+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|\end{array}\right)\right\}$$

Average similarity measure:

$$S_2(\Gamma,\Pi),(I,\Lambda)=1-\frac{1}{6}\left\{\begin{array}{c}\sum_{j=1}^{n}\frac{(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|)}{n}\\+Max_j\{(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|++|\Gamma^{**}\varphi_j-I^{**}\varphi_j|+)\}\end{array}\right\}$$

Convex similarity measure is presented as:

$$S_3(\Gamma,\Pi),(I,\Lambda)=1-\frac{1}{3}\left\{\alpha Max_j(|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|+|\Gamma^{**}\varphi_j-I^{**}\varphi_j|)+(1-\alpha)\left\{Min_j\left((|\Gamma\varphi_j-I\varphi_j|+|\Gamma^*\varphi_j-I^*\varphi_j|++|\Gamma^{**}\varphi_j-I^{**}\varphi_j|)\right)\right\}\right\}$$

This study applies intuitionistic fuzzy set (IFS)–based similarity measures to support rational and informed career determination for students by incorporating membership, non-membership, and hesitation degrees derived from academic performance across key subjects. Using maximin, average, and convex similarity measures, the similarity between four students and four potential career options—medicine, pharmacy, surgery, and anatomy—is systematically evaluated. The results consistently indicate that surgery emerges as the most suitable career choice for most students across all similarity measures, highlighting its robustness as a preferred option. While the maximin and average similarity measures show stable outcomes with minor variations, the convex similarity measure demonstrates sensitivity to the parameter α, revealing how changes in decision-maker emphasis influence career recommendations. Notably, at lower α values, anatomy and medicine occasionally become competitive alternatives, particularly for specific students, whereas higher α values reinforce surgery as the dominant choice. Overall, the analysis confirms that IFS-based similarity measures effectively capture uncertainty and partial knowledge in student performance, offering a flexible and reliable quantitative framework for career guidance and decision-making.

3. Distance, Similarity and Entropy measures for fuzzy soft set (FSS)

It discusses distance, similarity, and entropy measures for fuzzy soft set. Some distance measures are derived by using the concept of average, maximin and convexity by taking the modulus values of two sets. Further, some similarity measures are also proposed as these measures are useful to check whether the two sets are significantly similar. Under fuzzy soft settings, some entropy measures are also proposed using similarity measures. Finally, the proposed similarity measure is applied to a real-world decision-making problem.

Distance measures of FSS

The following distance measures are proposed for two fuzzy soft sets (Γ,Π) and (I,Λ)

Maximin distance measure:

$$D_1\big((\Gamma,\Pi),(I,\Lambda)\big) = Max_i\{Min_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\} \quad \dots (4.3.1)$$

Average distance measure:

$$D_2\big((\Gamma,\Pi),(I,\Lambda)\big) = \frac{1}{2m}\sum_{i=1}^{m}\left(\sum_{j=1}^{n}\left(\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|}{n}\right) + Max\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\right)$$

Convex distance measure:

$$D_3\big((\Gamma,\Pi),(I,\Lambda)\big) = Max_i\left\{\begin{matrix}\alpha Max_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\\ +(1-\alpha)Min_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\end{matrix}\right\}$$

Maximin similarity measure is presented as:

$$S_1\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - Max_i\{Min_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\} \quad \dots (4.3.3)$$

Average similarity measure is presented as:

$$S_2\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - \frac{1}{2m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\begin{matrix}\left(\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|}{n}\right)\\ +Max\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\end{matrix}\right\}$$

Convex Similarity Measure is presented as:

$$S_3\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - Max_i\{\alpha Max_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big) + (1-\alpha)Min_j\big(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j|\big)\}$$

Entropy measures for FSS

Let consider (Γ,Π) is a fuzzy soft set for all and $\varphi_j \in \Phi$, i=1,2…m and j=1,2…n then

Entropy based on Maximin Similarity Measure is presented as:

$$E_1(\Gamma,\Pi) = S_1\big((\Gamma,\Pi),(\Gamma^c,\Pi)\big) = 1 - Max_i\{Min_j\big(|2\Gamma_{\theta_i}\varphi_j - 1|\big)\}$$

Entropy based on Average second Similarity Measure is presented as:

$$E_2(\Gamma,\Pi) = S_2\big((\Gamma,\Pi),(\Gamma^c,\Pi)\big) = 1 - \frac{1}{2m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|\Gamma_{\theta_i}\varphi_j - \Gamma^c{}_{\theta_i}\varphi_j|}{n} + Max\big(|\Gamma_{\theta_i}\varphi_j - \Gamma^c{}_{\theta_i}\varphi_j|\big)\right\}$$

Entropy based on Convex Similarity Measure is presented as:

$$E_3(\Gamma,\Pi) = S_3\big((\Gamma,\Pi),(\Gamma^c,\Pi)\big) = 1 - Max_i\{\alpha Max_j\big(|\Gamma_{\theta_i}\varphi_j - \Gamma^c{}_{\theta_i}\varphi_j|\big) + (1-\alpha)Min_j\big(|\Gamma_{\theta_i}\varphi_j - \Gamma^c{}_{\theta_i}\varphi_j|\big)\}$$

The thesis highlights the application of fuzzy soft entropy and similarity measures as effective tools for decision-making under uncertainty. By modeling real-life problems such as investment selection and student award allocation, fuzzy soft sets capture the vagueness inherent in human judgment and multi-criteria evaluation. Entropy measures are used to assess the amount of information available for making reliable decisions, while similarity measures help compare alternatives against an ideal or reference model. The results demonstrate that these measures provide consistent and rational rankings, supporting optimal decision outcomes. Overall, the study confirms that fuzzy soft set–based entropy and similarity frameworks are robust, flexible, and well-suited for complex decision-making environments where precise information is difficult to obtain.

4. Distance, Similarity and Entropy measures for intuitionistic fuzzy soft set (IFSS)

Several fields dealing with the problem of uncertainty do not get fruitful results using fuzzy set theory, rough set theory, probability theory and other mathematical approaches. Then Soft set (SS) theory has been derived by Russian researcher Molodtsov (1999) that becomes very helpful to deal with the issues of uncertainty and vagueness. Further by taking hybridization of IFS and FSS distance, similarity and entropy measures are derived for IFSS. Firstly, distance measures are proposed by using the concept of average, maximin, convexity after then corresponding to proposed distance measures similarity measures are also derived. Based on these similarity measures, entropy measures are described for the intuitionistic fuzzy soft sets. Then a decision-making problem is also discussed by using entropy and similarity measures numerically.

Distance measures for IFSS

The following distance measures are proposed for two fuzzy soft sets (Γ,Π) and (I,Λ)

Maximin distance measure

$$D_1((\Gamma,\Pi),(I,\Lambda)) = Max_i\left\{Min_j\left(\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|}{2}\right)\right\}$$

Average distance measure

$$D_2((\Gamma,\Pi),(I,\Lambda)) = \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|}{n} + Max(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|)\right\}$$

Convex distance measure

$$D_3((\Gamma,\Pi),(I,\Lambda)) = Max_i\left\{\alpha Max_j\left(\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|}{2}\right) + (1-\alpha)Min_j\left(\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|}{2}\right)\right\}$$

Similarity measures for IFSS

Maximin similarity measure

$$S_1((\Gamma,\Pi),(I,\Lambda)) = 1 - \frac{1}{2}Max_i\{Min_j(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|)\}$$

Average similarity measure

$$S_2((\Gamma,\Pi),(I,\Lambda)) = 1 - \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|}{n} + Max(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|)\right\}$$

Convex similarity measure

$$S_3((\Gamma,\Pi),(I,\Lambda)) = 1 - \frac{1}{2}Max_i\{\alpha Max_j(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|) + (1-\alpha)Min_j(|\Gamma_{\theta_i}\varphi_j - I_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - I^*{}_{\theta_i}\varphi_j|)\}$$

Entropy measures for IFSS

Let consider (Γ,Π) is a fuzzy soft set for all and **φj Φ**, i=1,2…m and j=1,2…n then:

Maximin entropy measure

$$E_1((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \left(\frac{1}{2}\right)Max_i\{Min_j(|\Gamma_{\theta_i}\varphi_j - \Gamma^c{}_{\theta_i}\varphi_j| + |\Gamma^*{}_{\theta_i}\varphi_j - \Gamma^{*c}{}_{\theta_i}\varphi_j|)\}$$

$$= 1 - \left(\frac{1}{2}\right)Max_i\{Min_j(|2\Gamma_{\theta_i}\varphi_j - 1| + |2\Gamma^*{}_{\theta_i}\varphi_j - 1|)\}$$

Average entropy is presented as:

$$E_2((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|2\Gamma_{\theta_i}\varphi_j - 1| + |2\Gamma^*{}_{\theta_i}\varphi_j - 1|}{n} + Max(|2\Gamma_{\theta_i}\varphi_j - 1| + |2\Gamma^*{}_{\theta_i}\varphi_j - 1|)\right\}$$

Convex entropy is presented as:

$$E_3((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \left(\frac{1}{2}\right) Max_i\{\alpha Max_j(|2\Gamma_{\theta_i}\varphi_j - 1| + |2\Gamma^*{}_{\theta_i}\varphi_j - 1|) + (1 - \alpha) Min_j(|2\Gamma_{\theta_i}\varphi_j - 1| + |2\Gamma^*{}_{\theta_i}\varphi_j - 1|)\}$$

Intuitionistic fuzzy soft entropy measures play an important role in handling uncertainty and hesitation in real-world decision-making environments. In the context of market prediction, these measures effectively capture the attractiveness of different companies by simultaneously considering membership and non-membership information under multiple decision criteria. This approach enables investment organizations to evaluate alternatives in a structured and reliable manner, even when expert opinions and market conditions are imprecise or incomplete. The entropy- based analysis demonstrates that the available information is sufficient and consistent, thereby supporting confident investment decisions.

Similarly, intuitionistic fuzzy soft similarity measures provide a systematic framework for decision-making in personnel selection. When evaluating candidates foran information technology company, multiple qualitative attributes such as qualifications, skills, experience, and personality are assessed using intuitionistic fuzzy information obtained from different judges. By comparing these evaluations with an established standard derived from past experience, similarity measures help identify the most suitable candidates. The results indicate that the evaluations provided by one judge exhibit a higher degree of similarity to the standard, suggesting a better alignment with organizational expectations.

Overall, the intuitionistic fuzzy soft set framework proves to be highly effective for addressing complex decision-making problems characterized by vagueness and uncertainty. The development of distance, similarity, and entropy measures enhances the analytical capability of this framework. The applications discussed illustrate that intuitionistic fuzzy soft methods offer reliable and flexible tools for market analysis and human resource selection, thereby contributing significantly to informed and rational decision-making processes.

5. Distance, Similarity and Entropy measures for Interval-Valued Fuzzy Soft Set

Most of the time in real-life problems the membership value in FS is not significant or relevant. It is better to present interval-valued data to describe the membership degree of such sets. Yang et al. (2009) introduced the concept of IVFSS by combining IVFS and SS models. Recently, Yiara yong (2020) presented the idea of combining the theories of interval-valued FSS over semigroups. Alkhazaleh and Salleh (2012) discussed the idea of generalized IVFSS and their properties The problems in decision making area were also solved simultaneously by using similarity and distance measures for IVFSS by them. Alkhazaleh and Salleh (2011) gave the significant prospective soft set to intuitionistic FSS.

Distance measures for IVFSS

The following distance measures are proposed for two fuzzy soft sets (Γ,Π) and (I,Λ)

Maximin distance measure:

$$D_1((\Gamma,\Pi),(I,\Lambda)) = Max_i\left\{Min_j\left(\frac{|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|}{2}\right)\right\}$$

Average distance measure:

$$D_2((\Gamma,\Pi),(I,\Lambda)) = \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|}{n} + Max(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)\right\}$$

Convex distance measure:

$$D_3((\Gamma,\Pi),(I,\Lambda)) = Max_i\left\{\alpha Max_j\left(\frac{(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)}{2}\right) + (1-\alpha)Min_j\left(\frac{(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)}{2}\right)\right\}$$

Similarity Measures for IVFSS

Maximin similarity measure:

$$S_1((\Gamma,\Pi),(I,\Lambda)) = 1 - Max_i\left\{Min_j\left(\frac{|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|}{2}\right)\right\}$$

Average similarity measure:

$$S_2((\Gamma,\Pi),(I,\Lambda)) = 1 - \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|}{n} + Max(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)\right\}$$

Convex similarity measure:

$$S_3((\Gamma,\Pi),(I,\Lambda)) = 1 - Max_i\left\{\alpha Max_j\left(\frac{(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)}{2}\right) + (1-\alpha)Min_j\left(\frac{(|\Gamma^l{}_{\theta_i}\varphi_j - I^l{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - I^u{}_{\theta_i}\varphi_j|)}{2}\right)\right\}$$

Entropy measures for IVFSS

Maximin entropy is presented as:

$$E_1((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \left(\frac{1}{2}\right)Max_i\{Min_j(|\Gamma^l{}_{\theta_i}\varphi_j - \Gamma^{c\,l}{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - \Gamma^{c\,u}{}_{\theta_i}\varphi_j|)\}$$
$$= 1 - \left(\frac{1}{2}\right)Max_i\{Min_j(|2\Gamma^l{}_{\theta_i}\varphi_j - 1| + |2\Gamma^u{}_{\theta_i}\varphi_j - 1|)\}$$

Average entropy is presented as:

$$E_2((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \frac{1}{4m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{|2\Gamma^l{}_{\theta_i}\varphi_j - 1| + |2\Gamma^u{}_{\theta_i}\varphi_j - 1|}{n} + Max(|2\Gamma^l{}_{\theta_i}\varphi_j - 1| + |2\Gamma^u{}_{\theta_i}\varphi_j - 1|)\right\}$$

Convex entropy is presented as:

$$E_3((\Gamma,\Pi),(\Gamma^c,\Pi)) = 1 - \left(\frac{1}{2}\right)Max_i\{\alpha Max_j(|\Gamma^l{}_{\theta_i}\varphi_j - \Gamma^{c\,l}{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - \Gamma^{c\,u}{}_{\theta_i}\varphi_j|) + (1-\alpha)Min_j(|\Gamma^l{}_{\theta_i}\varphi_j - \Gamma^{c\,l}{}_{\theta_i}\varphi_j| + |\Gamma^u{}_{\theta_i}\varphi_j - \Gamma^{c\,u}{}_{\theta_i}\varphi_j|)\}$$
$$= 1 - \left(\frac{1}{2}\right)Max_i\{\alpha Max_j(|2\Gamma^l{}_{\theta_i}\varphi_j - 1| + |2\Gamma^u{}_{\theta_i}\varphi_j - 1|) + (1-\alpha)Min_j(|2\Gamma^l{}_{\theta_i}\varphi_j - 1| + |2\Gamma^u{}_{\theta_i}\varphi_j - 1|)\}$$

Interval-valued fuzzy soft set theory provides an effective framework for handling uncertainty and vagueness in emergency decision-making situations. In the case of a coal mine explosion accident, several emergency response plans are evaluated using benefit-based parameters such as gas concentration control, casualty reduction, smoke and dust management, feasibility of rescue operations, and restoration of damaged facilities. By representing expert assessments through interval-valued fuzzy information, the proposed entropy measures successfully quantify the amount of useful information contained in the data. The analysis shows that certain entropy measures yield higher informational content, while others contribute comparatively less, indicating their relative effectiveness in decision support.

Similarly, interval-valued fuzzy soft distance measures are applied to assess the severity of impact in regions affected by a tropical storm. Relief measures related to agriculture, livestock, fishermen, loss of life, alternative livelihood support, and ecological damage are evaluated using historical records and expert opinions. By comparing these assessments through distance measures, the approach clearly distinguishes between areas with different levels of impact. The results consistently indicate that one region is more severely affected and requires greater relief intervention than the other. This conclusion is further supported by existing normalized distance measures from the literature, confirming the reliability and robustness of the proposed approach.

Overall, decision-making under uncertain and complex conditions is significantly strengthened with interval-valued fuzzy soft entropy, distance, and similarity measures. These tools provide a systematic and consistent means of evaluating alternatives and identifying priorities in emergency management scenarios. The proposed measures can be further extended to develop additional information measures and may also be adapted to other hybrid soft set models, thereby offering wide applicability in future research and real-world decision-making problems.

6. Distance, Similarity and Entropy measures for Interval-Valued Fuzzy Soft Set

In this section by taking hybridization of IFS and IVFSS three different distance measures are defined along with their properties. Further based on these measures three similarity and entropy measures are also derived. Thereafter a hypothetical data is used to demonstrate applicability of proposed entropy measure in decision making. Finally, to check the validity of proposed distance measures, these measures are applied to the area of medical diagnosis.

Distance measures for IVIFSS

The following distance measures are proposed for two fuzzy soft sets (Γ,Π) and (I,Λ)

Maximin Distance Measure

$$D_1\big((\Gamma,\Pi),(I,\Lambda)\big) = \frac{1}{6}Max_i\Big\{Min_j\Big(\left|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j\right|\Big)\Big\}$$

Average Distance Measure

$$D_3\big((\Gamma,\Pi),(I,\Lambda)\big) = Max_i\left\{\alpha Max_j\left(\frac{\left(\begin{array}{c}\left|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j\right| \\ + \left|\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j\right| \\ + \left|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j\right|\end{array}\right)}{6}\right) + (1-\alpha)Min_j\left(\frac{\left(\begin{array}{c}\left|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j\right| \\ + \left|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j\right| + \left|\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j\right| \\ + \left|\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j\right| \\ + \left|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j\right|\end{array}\right)}{6}\right)\right\}$$

Convex Distance Measure

$$D_3\big((\Gamma,\Pi),(I,\Lambda)\big) = Max_i\left\{\alpha Max_j\left(\frac{\left(\begin{array}{c}|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| + |\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| + |\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\end{array}\right)}{6}\right) + (1-\alpha)Min_j\left(\frac{\left(\begin{array}{c}|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| + |\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\end{array}\right)}{6}\right)\right\}$$

Similarity measures for IVIFSS

Maximin similarity measure :

$$S_1\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - \frac{1}{6}Max_i\left\{Min_j\left(\begin{array}{c}|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| + |\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\end{array}\right)\right\}$$

Average similarity measure:

$$S_2\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - \frac{1}{12m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{\begin{array}{c}|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| + |\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| + |\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| + |\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\end{array}}{n} + Max\big(|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| + |\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| + |\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| + |\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| + |\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\big)\right\}$$

Convex similarity measure

$$S_3\big((\Gamma,\Pi),(I,\Lambda)\big) = 1 - Max_i\left\{\alpha Max_j\left(\frac{\left(\begin{array}{c}|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| + |\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| \\ +|\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| + |\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| + |\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\end{array}\right)}{6}\right) + (1-\alpha)Min_j\left(\frac{\big(|\Gamma^{l}{}_{\theta_i}\varphi_j - I^{l}{}_{\theta_i}\varphi_j| + |\Gamma^{u}{}_{\theta_i}\varphi_j - I^{u}{}_{\theta_i}\varphi_j| + |\Gamma^{l^*}{}_{\theta_i}\varphi_j - I^{l^*}{}_{\theta_i}\varphi_j| + |\Gamma^{u^*}{}_{\theta_i}\varphi_j - I^{u^*}{}_{\theta_i}\varphi_j| + |\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - I^{l^{**}}{}_{\theta_i}\varphi_j| + |\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - I^{u^{**}}{}_{\theta_i}\varphi_j|\big)}{6}\right)\right\}$$

Entropy measures for IVIFSS

Maximin Entropy Measure

$$E_1\big((\Gamma,\Pi),(\Gamma^c,\Lambda)\big) = 1 - \left(\frac{1}{6}\right)Max_i\big\{Min_j\big(|2\Gamma^{l}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{l^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - 1|\big)\big\}$$

Average entropy measures

$$E_2\big((\Gamma,\Pi),(\Gamma^c,\Lambda)\big) = 1 - \frac{1}{12m}\sum_{i=1}^{m}\left\{\sum_{j=1}^{n}\frac{\begin{array}{c}|2\Gamma^{l}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u}{}_{\theta_i}\varphi_j - 1| \\ +|2\Gamma^{l^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - 1|\end{array}}{n} + Max\big(|2\Gamma^{l}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{l^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^*}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{l^{**}}{}_{\theta_i}\varphi_j - 1| + |2\Gamma^{u^{**}}{}_{\theta_i}\varphi_j - 1|\big)\right\}$$

Convex entropy measure

$$E_3\left((\Gamma,\Pi),(\Gamma^c,\Lambda)\right) = 1 - \frac{1}{6} Max_i \left\{ \alpha Max_j \left(\begin{array}{c} \left|2\Gamma^{l}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{u}{}_{\theta_i\varphi_j} - 1\right| \\ + \left|2\Gamma^{*l}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{*u}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{l^{**}}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{u^{**}}{}_{\theta_i\varphi_j} - 1\right| \end{array} \right) + (1-\alpha) Min_j \left(\left|2\Gamma^{l}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{u}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{*l}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{*u}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{l^{**}}{}_{\theta_i\varphi_j} - 1\right| + \left|2\Gamma^{u^{**}}{}_{\theta_i\varphi_j} - 1\right| \right) \right\}$$

Interval-valued intuitionistic fuzzy soft entropy measures provide an effective mechanism for decision-making problems in situations where information is imprecise and evaluations are expressed in ranges rather than exact values. In the context of house selection, the attractiveness of different houses is assessed using qualitative parameters such as cost, aesthetics, material quality, maintenance condition, and surrounding environment. Since exact evaluations are difficult to obtain, interval-valued intuitionistic fuzzy soft sets successfully capture the uncertainty associated with human judgment. The entropy analysis reveals that certain entropy measures extract more informative content from the data, while others contribute comparatively less, thereby highlighting their relative effectiveness in decision support.

The applicability of interval-valued intuitionistic fuzzy soft distance measures is further demonstrated in the field of medical diagnosis. Here, patient symptoms are compared with predefined diagnostic patterns representing different diseases. By calculating distances between the patient profile and diagnostic profiles, the proposed measures assist in identifying the most plausible diagnosis. The results show that different distance measures may lead to different diagnostic conclusions, offering a broader perspective for clinical decision-making. In contrast, existing normalized distance measures from the literature provide limited discrimination, whereas the proposed measures offer clearer and more reliable insights.

Overall, interval-valued intuitionistic fuzzy soft set theory represents a powerful integration of interval-valued intuitionistic fuzzy sets and soft set theory. The development of distance, similarity, and entropy measures within this framework significantly enhances its analytical capability. The applications presented illustrate the robustness and flexibility of the proposed measures in decision-making and medical diagnosis under uncertainty. These methods can be further extended to develop additional information measures and adapted to other hybrid soft set models, thereby opening new directions for future research.

CONCLUSION

The present doctoral research has made a significant contribution to the domain of information theory by systematically developing and analyzing hybrid information theoretic measures capable of handling multiple forms of uncertainty encountered in real-world data. Traditional probabilistic information measures, though mathematically elegant and widely applicable, rely heavily on precise probability distributions and therefore fall short when confronted with vagueness, ambiguity, incompleteness, and subjectivity. This research successfully addresses these limitations by integrating information theory with fuzzy sets, rough sets, soft sets, intuitionistic fuzzy sets, and their interval-valued and hybrid extensions.

A comprehensive framework for non-probabilistic and hybrid entropy, distance, and similarity measures has been proposed. The theoretical foundations of these measures were rigorously established through axiomatic definitions and mathematical proofs, ensuring essential properties such as non-negativity, boundedness, symmetry, monotonicity, and consistency. The inclusion of hesitation, boundary regions, and parameterization significantly enhances the expressive power of the proposed measures compared to classical significantly enhances the expressive power of the proposed measures compared to classical counterparts.

The applicability and effectiveness of the develop measures were demonstrated through their use in data mining tasks, including feature selection, attribute reduction, and pattern classification, as well as in decision-making and medical diagnosis problems. The results indicate that hybrid information theoretic measures provide improved robustness, better discrimination capability, and higher interpretability when dealing with uncertain and imprecise data. In particular, the integration of fuzzy, rough, and soft computing paradigms enables a more realistic representation of real-world knowledge systems.

Overall, the research confirms that hybrid information theoretic approaches constitute a powerful and flexible alternative to probabilistic methods, especially in complex environments where uncertainty cannot be adequately captured by probability alone. The outcomes of this study not only enrich the theoretical literature but also offer practical tools for researchers and practitioners working in data analytics, artificial intelligence, and decision support systems.

FUTURE SCOPE

While the present research provides a strong theoretical and application-oriented foundation, several promising directions remain open for further investigation:

1. Extension to Dynamic and Time-Dependent Data: The proposed measures can be extended to dynamic environments where data evolve over time. Developing entropy and similarity measures for temporal fuzzy, rough, or intuitionistic frameworks would be particularly useful for real-time decision-making, financial forecasting, and monitoring systems.

2. Integration with Machine Learning and Deep Learning Models: Future research may explore the incorporation of hybrid information theoretic measures into machine learning algorithms such as clustering, classification, ensemble learning, and deep neural networks. These measures can be used as loss functions, feature selection criteria, or similarity metrics to enhance model interpretability and robustness.

3. Big Data and High-Dimensional Applications: With the increasing availability of large-scale and high-dimensional datasets, there is scope to adapt the proposed measures for big data environments. Optimization technique sand parallel computing strategies may be employed to improve computational efficiency and scalability.

4. Development of Decision Support Systems: The hybrid measures can be embedded into intelligent decision support systems for applications in healthcare, supply chain management, risk assessment, and policy analysis. User-friendly software tools and visualization techniques may further enhance practical usability.

5. Uncertainty Modelling in Emerging Domains: Emerging fields such as Internet of Things (IoT), cyber-physical systems, social network analysis, and smart cities involve heterogeneous and uncertain data sources. The proposed framework can be extended to model uncertainty in these complex systems.

6. Further Theoretical Generalizations: Future work may focus on developing new axiomatic systems and generalized hybrid frameworks by combining intuitionistic, neutrosophic, and plithogenic sets with information theory. Such extensions could provide even richer representations of indeterminacy and contradiction.

7. Real Data: Future research may focus on systematic primary real data collection through surveys, expert evaluations, field observations, and institutional records to validate and refine hybrid information theoretic measures, ensuring their robustness, adaptability, and practical relevance under real-world uncertainty and incomplete information scenarios.

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