अनुसंधान

# Anusandhan

NDIM's Journal of Business and Management Research

Vol. VIII, Issue 2, August 2026

ISSN No. 2581-8120

ICSSR Sponsored

Indian Council of Social Science Research

Guru Gobind Singh Indraprastha University

Crossref.ID/DOI-10.56411

New Delhi Institute of Management

Anusandhan: NDIM's

*Journal of*

# Business and Management Research

Vol. VIII, Issue 2, August 2026

ISSN No. 2581-8120

अनुसंधान
# Anusandhan
NDIM's Journal of Business and Management Research

# Outcomes

### 1. Article 1: Exploring the Relationship between Green Revenue and Corporate Reputation: Evidence from India

This study demonstrates that green revenue has a significant positive influence on the corporate reputation of Indian listed companies. The findings highlight that environmentally responsible business practices enhance stakeholder trust, market value, and long-term competitiveness. The research provides valuable insights for firms, investors, and policymakers in promoting sustainable business growth.

### 2. Article 2: Technology-Enabled Social Innovation for Sustainable Community Development

This paper highlights how emerging technologies such as Artificial Intelligence, blockchain, IoT, and digital platforms can drive inclusive and sustainable community development. It emphasizes that technology-enabled social innovation improves governance, service delivery, and community participation while strengthening resilience. The study encourages policymakers to adopt ethical, people-centric, and collaborative digital solutions for long-term societal impact.

### 3. Article 3: Unleashing the Potential of Artificial Intelligence in Human Resource Management

This study reveals that Artificial Intelligence is transforming human resource management by improving recruitment, talent acquisition, employee engagement, and learning processes. The findings confirm that AI adoption positively influences HRM practices, particularly in talent recruitment and organizational efficiency. The research encourages organizations to integrate AI responsibly to build agile, productive, and future-ready workplaces.

### 4. Article 4: Attachment Styles and Reflective Functioning as Predictors of Emotion Regulation and Management among Indian Youth

This study examines how attachment styles and reflective functioning influence emotion regulation among Indian youth. The findings indicate that reflective functioning significantly predicts emotional regulation flexibility, whereas attachment styles alone have limited predictive value. The research offers practical implications for counselling centres and educational institutions to strengthen emotional well-being through reflective interventions.

**5. Article 5: Behavioural Biases and Pension Investment Decisions: Evidence from Employees in Kerala**

This study investigates the influence of behavioural biases on pension investment decisions among employees in Kerala. The findings reveal that although several behavioural biases are prevalent, present bias has the strongest negative impact on retirement planning and investment behaviour. The study recommends improving financial literacy and behavioural awareness to encourage informed and sustainable pension investment decisions.

**6. Article 6: Dynamic Spillovers between Cryptocurrencies and BRICS Equity Markets: A TVP-VAR Analysis**

This study explores the dynamic return spillovers between major cryptocurrencies and BRICS equity markets using the TVP-VAR approach. The findings identify cryptocurrencies, particularly Ethereum, as major transmitters of market shocks, while the Indian equity market emerges as one of the most affected receivers. The research provides valuable insights for investors, portfolio managers, and policymakers in managing financial market integration and investment risk.

**Book Review: Impact of Blockchain in HRM**

The book review highlights the transformative role of blockchain technology in modern Human Resource Management. It explains how blockchain enhances recruitment, credential verification, payroll management, and employee data security while improving transparency and operational efficiency. The review encourages HR professionals to explore blockchain as a strategic tool for building secure, trustworthy, and technology-driven HR systems.

## Chairperson Message

It gives me immense pleasure to present the latest issue of **ICSSR Sponsored** *Anusandhan: NDIM's Journal of Business and Management Research* Volume VIII, Issue 2, August 2026. At New Delhi Institute of Management, we firmly believe that research is the cornerstone of academic excellence and a catalyst for meaningful societal and organizational transformation. Through *Anusandhan*, we strive to create an intellectual platform where innovative ideas, evidence-based research, and interdisciplinary perspectives converge to address contemporary business and management challenges.

**First paper** is on Exploring the Relationship between Green Revenue and Corporate Reputation: Evidence from India by Sougata Mondal, from University of Calcutta and Sanjib Mitra from Sarsuna College, West Bengal, India

**Second paper** is on Technology-Enabled Social Innovation for Sustainable Community Development by Rajeev Kumar, from Doon University, Dehradun, Uttarakhand

**Third paper** is on Unleashing The Potential Of Artificial Intelligence In Human Resource Management by Isha Kataria and Kavita Malik from Maharshi Dayanand University, Rohtak, Haryana, India.

**Fourth paper** is on Attachment Styles and Reflective Functioning as Predictors of Emotion Regulation and Management among Indian Youth by Deepanshi Garg and Mamata Mahapatra from Amity University Uttar Pradesh Noida, UP

**Fifth paper** is on Behavioural Biases And Pension Investment Decisions: Evidence From Employees In Kerala by Sajitha S M, and Nimi Dev R, from Govt. College foe Women, University of Kerala Thiruvananthapuram.

**Sixth Paper** is on Cryptocurrency-BRICS Equity Spillovers: Evidence of Market Integration Using TVP-VAR Analysis by Garima Anand, Bharti and Ashish Kumar from GGSIP University, Delhi

**Book review** on Impact of Blockchain Sixth Paper in HRM by Divya Kataria, IT Professional, Faridabad, Haryana.

I extend my sincere appreciation to our contributors, reviewers, editorial board, and publication team for their dedication and scholarly commitment.

I am confident that this issue will inspire critical thinking, encourage collaborative research, and motivate scholars to generate knowledge that advances academia, industry, and society.

I wish our readers an engaging, enriching, and intellectually rewarding reading experience.

**Dr. Bindu Kumar**
Chairperson, NDIM

## From the Editorial Desk

Welcome to the latest issue of **ICSSR Sponsored** Anusandhan: NDIM's Journal of Business and Management Research Volume VIII, Issue 2, August 2026. As a double-blind peer-reviewed journal, Anusandhan is committed to advancing high-quality research that bridges academic inquiry with managerial practice. This issue reflects our continued endeavour to publish original and relevant scholarship addressing emerging challenges across business, management, technology, finance, sustainability, and the social sciences.

This volume opens with an insightful study on green revenue and corporate reputation, highlighting the growing importance of sustainability as a strategic driver of organizational performance. The second paper explores technology-enabled social innovation, presenting digital technologies as powerful enablers of inclusive growth and sustainable community development.

Recognising the transformative impact of Artificial Intelligence on organizations, the third article examines AI-driven innovations in Human Resource Management. It discusses how intelligent technologies are reshaping recruitment, performance management, employee learning, and organizational effectiveness while identifying opportunities and future challenges.

The present issue reflects this vision by bringing together scholarly contributions that span sustainability, technology, human behaviour, finance, and organizational development. The opening article explores the relationship between green revenue and corporate reputation, highlighting how sustainable business practices have become integral to long-term organizational success. The subsequent paper examines technology-enabled social innovation, demonstrating how digital transformation can empower communities and contribute to sustainable development.

We express our heartfelt gratitude to all authors, reviewers, members of the Editorial Board, and the Research Cell of NDIM for their invaluable contributions. We hope this issue stimulates scholarly dialogue, encourages interdisciplinary collaboration, and inspires future research that creates meaningful academic, professional, and societal impact. The successful publication of this issue of Anusandhan: NDIM's Journal of Business and Management Research is the result of the collective efforts of many dedicated individuals. We extend our heartfelt gratitude to all the authors for sharing their original research and valuable insights, and to our reviewers for their thoughtful evaluations and constructive feedback that strengthened every manuscript. We also sincerely appreciate the unwavering support of the Editorial Board, the Research Cell, faculty members, and the publication team, whose commitment and meticulous efforts made this issue possible. Your passion for advancing knowledge continues to strengthen the culture of research and academic excellence at NDIM.

Warm regards,
**Prof. (Dr.) Madhu Arora**
*Editor-in-Chief*
*Anusandhan: NDIM's Journal of Business and Management Research*

# Contents

## Anusandhan: NDIM's Journal of Business and Management Research

http://doi.org/10.56411/anusandhan.2026.v8i1.1-7

# Exploring the Relationship between Green Revenue and Corporate Reputation: Evidence from India

Sougata Mondal

UGC-Senior Research Fellow, University of Calcutta

Dr. Sanjib Mitra

Associate Professor, Department of Commerce, Sarsuna College,
Address: Sarsuna, Kolkata: 700061, West Bengal, India

**Sougata Mondal, ORCID ID : 0009-0008-6331-6615**
**Dr. Sanjib Mitra, ORCID ID : 0009-0003-9044-7614**

**Date of receiving the manuscript: Feb 6, 2026** **Date of publication: August 31, 2026**

**Abstract:** This study aims to understand whether any relationship exists between green revenue and reputation of India's listed firms. It considers the sixty top performing companies in terms of their percentage of green revenue as extracted from LSEG database. The study period of nine years ranges from 2015-16 to 2023-24. Econometric tools such as correlation analysis and dynamic panel data regression analysis are applied for generating empirical outcomes. The regression result confirms that green revenue has significant positive influence on the corporate reputation of select companies in India.

**Keywords:** Green revenue, Corporate Reputation, Dynamic Panel Data Analysis, India.

## 1. Introduction & Background

One of the biggest threats to humanity is climate change (Dellink et al., 2019). A major international credit rating agency, Moody's Analytics, estimated that between 33 to 38 percent of business assets worldwide are at danger due to climate change. In response to the growing stringency of international legislation and agreements aimed at preventing environmental degradation, companies are adopting initiatives and strategies to carry out environmentally responsible business practices. One potential method to ensure environmental sustainability is for the investors who prioritize returns to integrate environmental and social issues into their financial and decision-making procedures (Keefe, 2007). Due to growing pressure from customers, regulators, employees, and investors to take on environmental accountability, companies are transitioning from a reactive approach driven by regulations to a proactive approach that goes beyond mere compliance in environmental management (Khanna & Damon 1999; Ervin et al. 2013). The incorporation of green initiatives by businesses has always been associated with the standpoint of corporate social responsibility (CSR) and sustainable investment. Previously, the conventional economic theories posit that enterprises would only get partial advantages from investing in the environment, resulting to a disadvantage for firms to allocate sufficient resources towards environmental investments.

On the other hand, several writers, including Porter (1991) and Porter & Van der Linde (1995), have contended that more strict regulation towards sustainability may actually enhance business profitability in the long term. This is achieved by compelling enterprises to prioritize the reduction of production costs and the improvement of customer satisfaction and sales.

Not only in the developed nations but also in a developing nation like India enterprises have been gradually acknowledging the organized framework of environmental management techniques. The Prime Minister of India announced that India is committed to attain the Net Zero emission target by 2070 and the non-fossil fuel-based cumulative electrically powered installed capacity to be boosted to 50% by 2030. A PwC survey on Indian corporates revealed that 51% of India's top 100 corporations have begun publishing their emissions of carbon voluntarily, with 31% sharing their net-zero ambitions. With new ESG rules, India's shift to Business Responsibility and Sustainability Report (BRSR) indicates its dedication towards sustainability reporting.

There exists various empirical research on environmental perspective studying the influence of a business's environmental performance on firm value, profitability, risks, etc. However, no such study has been found which discusses the link between green revenue and corporate reputation of firms. Hence, the present study is a humble attempt to examine the influence of environmental activities on the reputation of Indian firms.

## 2. Literature Review

The impact of a firm's green revenue on corporate reputation is multifaceted. Research indicates that higher green revenue can enhance a firm's reputation, as it signals commitment to sustainability, which is increasingly valued by consumers and investors. This relationship is supported by various studies that highlight the importance of green initiatives in shaping corporate image and performance. Seo and Cordeiro (2025) found that firms with significant green revenue often enjoy a better reputation due to perceived environmental responsibility, which can lead to increased customer loyalty and market share. A study by Guo and Zhong (2023) showed that higher green revenue correlated with improved firm valuation and reduced cash holdings, indicating that investors might favour companies with strong sustainability practices. Jesika and Putri (2025) found that the integration of green manufacturing and Corporate Social Responsibility (CSR) significantly enhance corporate reputation, which in turn positively affect overall company performance. Another study by Juwita et al. (2024) showed that effective green marketing communication and the use of environmental friendly materials are crucial for enhancing corporate reputation and profitability, demonstrating the strategic importance of sustainability in branding. Across different countries, Lee (2012) found that firms that adopted green strategies and emphasized their corporate reputation tend to perform better economically, showcasing the global relevance of sustainability in business practices. A study by Kim et al. (2024) highlighted that overall ESG management significantly influences corporate reputation, suggesting that environmental responsibility may play a role in shaping perceptions. Chen et al., (2024) indicated a negative moderating effect of corporate reputation on the ESG-financial performance relationship, suggesting that while green technology innovation enhanced performance, a higher corporate reputation might weaken the impact of green revenue on overall corporate success. Conversely, Cordeiro, (2025) revealed that while green revenue can bolster reputation, it may not always reflect actual environmental performance, as firms with poor environmental outcomes can still achieve high reputational scores through effective communication and marketing strategies. Recently, a study by Martin-Melero et al. (2026) found that ESG compliance enhanced business reputation and attracted talents. This highlights the complexity of the relationship between perceived and actual corporate greenness. Thus, the hypothesis of this study is:

$H_0$: There is no impact of green revenue on corporate reputation.

$H_1$: There is a significant impact of green revenue on corporate reputation.

***Research Gap***

The literature review confirms the lack of research to find the link between green revenue and corporate reputation. Hence, it offers a fresh door to explore the region more intrinsically. Most of the research is from developed economies, which further advises investigating this link from a developing economy, such as India. Therefore, the current research aims to close these gaps and examine how the green revenue of Indian firms affects its reputation in capital market.

## 3. Research Objectives

To fill the above research gaps, the research objective is identified as to understand how green revenue of Indian companies affect its reputation.

## 4. Data and Methodology

***Sample & Study Period***

Using a non probability based judgmental sampling method, out of India's Top sixty companies in terms of their percentage of green revenue; forty eight companies have been selected for the final sample based on the availability of relevant data. The study relies on secondary data which have been retrieved from ACE Equity and LSEG databases. Data regarding Green revenue percentage is collated from the LSEG database and other relevant financial data are retrieved from the ACE Equity database. The mandatory provisions for CSR came into existence in India from F.Y. 2014-15. Hence, the study period of nine years ranges from 2015-16 to 2023-24.

***Variables & Models***

To meet the research objectives following dependent, independent and control variables, as mentioned in Table 1 are chosen.

**Table 1**

| Variable Type | Variable Name | Description |
|---|---|---|
| Dependent | Market Capitalization | Corporate reputation (CR) |
| Independent | Percentage of Green Revenue | As calculated by LSEG database (GR) |
| Control | Return on Assets | Profitability (PRF) |
| | Debt to Equity Ratio | Leverage (LEV) |
| | Natural log of Total Assets | Size of company (SIZE) |

*Source:* Compiled by authors

Panel data analysis approach is applied to generate the empirical results. The benefit of adopting this approach is that it allows for large number of observations, hence help in finding the effects that would be difficult to identify through pure cross-sectional or time-series analysis. This approach also contributes to greater efficiency, more degrees of freedom, less collinearity across variables, and more variability. Additionally, panel data technique assists in adjusting for individual heterogeneity (Baltagi, 2005). Dynamic panel regression method has been used here to handle heterogeneity and endogeneity issues.

The following research model is formed for empirical testing:

$$CR_{i,t} = \alpha_0 + \alpha_1 CR_{i,t-1} + \alpha_2 GR_{i,t} + \sum \alpha_j ControlVariables_{i,t} + \varepsilon_{i,t}$$

Here, intercept is $\alpha_0$, composite error term is $\varepsilon_{i,t}$, whereas, i implies firm, and t refers to year for the model.

System Generalised Method of Moments (GMM) of the dynamic panel regression method is a tool for estimating dynamic panels with lagged levels and lagged initial differences for a system of equations. Additionally, it handles endogeneity and produces better results than OLS. Two diagnostic tests are essential to validate the system GMM – (i) autocorrelation test for error components and (ii) Hansen test (1982) for checking endogeneity (Arellano & Bond, 1991). Table 4 represents the results of two-step system GMM using Arellano-Bover/ Blundell-Bond estimation using the 'xtdpdsys' command in Stata 17.0.

### *Empirical Results & Analysis*

**Table 2.** Descriptive Statistics

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| **CR** | 423 | 29224.17 | 89153.44 | 0 | 802168.3 |
| **GR** | 423 | 29.94194 | 32.07921 | 0 | 100 |
| **PROF** | 423 | – 0.1096948 | 73.82665 | – 1154.825 | 230.2046 |
| **LEV** | 423 | 0.8709693 | 6.010515 | -54.69 | 66.7 |
| **SIZE** | 423 | 7.419461 | 2.183789 | 1.490654 | 13.12641 |

*Source:* Compiled by authors

The descriptive statistics of the variables are shown in Table 2. The dependent variable, CR has a mean value of Rs. 29224.17 with a high standard deviation of 89153.44 and its maximum and minimum values range between 802168.3 and 0. GR, the independent variable has the mean value of 29.94% with maximum and minimum values being 100% and 0, respectively. All the three control variables are measured with the same parameters.

**Table 3.** Correlation Analysis

| Variables | CR | GR | PROF | LEV | SIZE |
|---|---|---|---|---|---|
| **CR** | 1.0000 | | | | |
| ***P value*** | | | | | |
| **GR** | – 0.0006 | 1.0000 | | | |
| ***P value*** | *0.9901* | | | | |
| **PROF** | 0.0964* | – 0.0156 | 1.0000 | | |
| ***P value*** | *0.0476* | *0.7497* | | | |

| Variables | CR | GR | PROF | LEV | SIZE |
|---|---|---|---|---|---|
| **LEV** | – 0.0360 | – 0.0544 | 0.0134 | 1.0000 | |
| ***P value*** | *0.4599* | *0.2639* | *0.7832* | | |
| **SIZE** | 0.4762* | 0.0094 | 0.2449* | 0.0181 | 1.0000 |
| ***P value*** | *0.0000* | *0.8471* | *0.0000* | *0.7105* | |

** shows significance at $p < 0.05$*

*Source:* Compiled by authors

Table 3 shows the pairwise correlation matrix. An insignificant correlation exists between the CR and GR. No serious multi-collinearity issue can be found in this table.

**Table 4.** Regression Analysis

| CR | Coefficient | Std. err. | Z | P>z |
|---|---|---|---|---|
| **CR $_{(t-1)}$** | 0.7144386 | 0.0001719 | 4156.84 | 0.000 |
| **GR** | 166.3491 | 2.003924 | 83.01 | 0.000 |
| **PROF** | – 67.39812 | 2.846933 | – 23.67 | 0.000 |
| **LEV** | – 57.31831 | 29.23433 | – 1.96 | 0.050 |
| **SIZE** | 26513.94 | 96.27706 | 275.39 | 0.000 |
| **Constant** | – 190667.5 | 1124.256 | – 169.59 | 0.000 |

Number of Observations: 376

Number of groups: 47

Number of instruments: 40

AR (2): – 0.46324, Prob > z: 0.6432

Sargan test: 37.03163, Prob > chi2: 0.3308

*Source:* Compiled by authors

Table 4 displays the dynamic panel data regression result. The result shows that the GR has a positive and statistically significant relationship with the CR. It implies that increase in green revenue of the Indian companies can enhance their corporate reputation. The results are inline with the studies of Kim et al. (2024), Guo and Zhong (2023), and Jesika and Putri (2025) but not support the results as revealed by Chen et al., (2024) and Cordeiro, (2025).Therefore, the firms should focus on practicing more green activities, that in turn, can help to raise its market capitalisation. It may be due to the fact that green revenue enhances market capitalisation by signalling robust potential in the growing green economy, thereby attracting conscientious investors pursuing profitable and environmental solutions, which results in a reduced cost of capital and increased investor inflows. The 'green alpha' is propelled by increasing demand for eco-friendly goods, favourable government regulations, and the impression of reduced risk, which investors compensate with elevated values, despite standard financial measurements potentially failing to encompass the whole value. Additionally, it can be seen that all the control variables have significant impact on the CR. The coefficient of lag value of the dependent variable is significant. It shows the dynamic nature of the research model. Again, the number of instruments is less than the number of groups, which is desirable for the regression model. Again, for validating the dynamic panel data model, two post estimation tests are necessary. Firstly, the insignificant value of the AR (2) test confirms the absence of autocorrelation and secondly, the statistically insignificance of the Sargan test implies that the instrument variables are exogenous and valid, i.e. not correlated with the error term.

## 5. Conclusion, Implications, and Limitations

This research aimed to gather empirical evidence about the connection between green revenue and reputation of companies in a developing nation, India. A significant limitation of previous empirical research on this area is the scarcity of evidence about dynamic impacts, especially when using panel data. Therefore, the present study provides dynamic panel data analysis based on data from forty-eight top companies, listed in India's capital market, in terms of their percentage of green revenue. The study provides new evidence on the debate, that is, whether investment in green activities result into improvement in firm's reputation.

### *Implications*

The empirical evidence provides that the percentage of green revenue of the select companies affects positively on the corporate reputation which is also statistically significant. Hence, the null hypothesis of the study is rejected. It is evident that, in India, a company, which is conscious of the environment, can gain the trust of various stakeholders by enhancing its reputation in the capital market. It may be due to the fact that green revenue bolsters the image of enterprises in India by highlighting a dedication to environmental stewardship, aligning with the principles of more environmentally conscious stakeholders. As India handles the intricate balance between economic advancement and environmental issues, enterprises that adopt sustainable practices are seen as ethical, robust, and progressive. The outcomes provide new insights for firms, investors, and policymakers that can be useful for their decision-making regarding environmental sustainability. For instance, in order to achieve green transformation, businesses should fully use market practices that will improve their image and ability to take risks. Again, governments need to enact more stringent and revolutionary climate measures. Additionally, investors must focus on environmentally friendly companies to invest for a sustainable future return.

### *Limitations*

The study suffers from several limitations that can be addressed in further research. Firstly, the sample size is very small as compared to the large number of listed firms in India. It can be increased in future study. Secondly, other models of dynamic panel data can deliver different results. Thirdly, no causal relationship between these two areas is established; that can also be addressed in future.

## References


- Chen, X., Lakkanawanit, P., Suttipun, M., Swatdikun, T., & Huang, S. (2024). Green Technology Innovation and Corporate Reputation: Key Drivers of ESG and Firm Performance. *Emerging Science Journal*, *8*(6), 2501–2518. https://doi.org/10.28991/esj-2024-08-06-021
- Ervin, D., J. Wu, M. Khanna, C. Jones, and T. Wirkkala. 2013. "Motivations and Barriers to Corporate Environmental Management." Business Strategy and the Environment 22 (6): 390–409. https://doi:10.1002/bse.1752
- Guo, C., & Zhong, R. (2023). *Is Green Revenue Vanity or Sanity? Evidence from Corporate Cash*

*Holdings*. https://doi.org/10.2139/ssrn.4670331

- Jesika, N., & Putri, F. R. (2025). Green Manufacturing and CSR in Enhancing Firm Performance: The Mediating Role of Firm Reputation. *Research Horizon*, *5*(3), 587–598. https://doi.org/10.54518/rh.5.3.2025.601
- Juwita, R., Rizaldy, R., & Yoga, T. (2024). *The Impact of the Use of Environmentally Friendly Raw Materials and Green Marketing Communication on Corporate Reputation and Profitability in the Manufacturing Industry in Central Java*. https://doi.org/10.58812/wsshs.v2i08.1182
- Keefe JF. 2007. From SRI to sustainable investing. GreenMoney Journal. http://archives.greenmoneyjournal.com/article.mpl?newsletterid=41&articleid=544 [10 May 2014].
- Khanna, M., and L. Damon. 1999. "EPA's Voluntary 33/50 Program: Impact on Toxic Releases and Economic Performance of Firms." Journal of Environmental Economics and Management 37 (1): 1–25. https://doi:10.1006/jeem.1998.1057.
- Kim, J., Gim, G.-Y., Lee, H., & Zul-Erdene, D. (2024). *The Impact of Company's ESG Activities on Corporate Reputation* (pp. 131–141). Springer Nature. https://doi.org/10.1007/978-3-031-53385-3_11
- Lee, J. (2012). A Global Perspective on Green Sustainability, Corporate Reputation, and Technological Strength for Firm Performance Across Countries. *Journal of Distribution Science*, *10*(8), 15–23. https://doi.org/10.15722/JDS.10.8.201208.15
- Martin-Melero, I., Medrano-Garcia, M. L., Hernandez-Perlines, F., & Gomez-Martinez, R. (2026). ESG and reputation in Ibero–America: Evidence from corporate rankings. *International Entrepreneurship and Management Journal*, *22*(1). https://doi.org/10.1007/s11365-026-01165-1
- Porter, M. 1991. "American's Greening Strategy." Scientific American 264 (4): 168–168. https://doi:10.1038/scientificamerican0491-168
- Porter, M., and C. Van der Linde. 1995. "Green and Competitive." Harvard Business Review 73 (5): 120–134.
- PwC India Report. (2024, April). Retrieved May 17, 2024, from https://www.pwc.in/press-releases/2024/51-of-indias-top-100-listed-companies-disclosed-their-scope-3-data-for-fy23-despite-it-being-a-voluntary-disclosure-in-the-brsr-pwc-india-report.html
- Seo, J. Y., & Cordeiro, J. J. (2025). Corporate green reputations and environmental performance: An analysis of the Newsweek's green rankings data. *Management Research Review*, *48*(9), 1405–1429. https://doi.org/10.1108/MRR-03-2025-0169

Anusandhan: NDIM's Journal of Business and Management Research | ISSN No. 2581-8120, Vol. VIII, Issue 2, August 2026

http://doi.org/10.56411/anusandhan.2026.v8i1.08-15

# Technology-Enabled Social Innovation for Sustainable Community Development

Dr. Rajeev Kumar

School of Management, Doon University,
Dehradun (Uttarakhand)

**ORCID ID : 0000-0003-2217-1145**

**Date of receiving the manuscript: March 12, 2026** **Date of publication: August 31, 2026**

**Abstract:** Technology-enabled social innovation (TESI) has emerged as a critical approach for addressing complex societal challenges and fostering sustainable community development. This study aims to examine the role of TESI in enhancing access to information, improving governance and local economic systems, advancing participatory planning, and supporting environmental sustainability. The research adopts a research design based on existing literature and case studies, drawing on a purposive sample of relevant global TESI initiatives. Literature was analyzed to identify key patterns, trends, and impacts of technology integration in community-driven development processes. The findings highlight that advanced technologies such as artificial intelligence (AI), mobile platforms, blockchain, digital twins, and the Internet of Things (IoT) significantly contribute to designing, implementing, and scaling innovative social solutions. Beyond technological efficiency, TESI promotes inclusivity, participation, and empowerment, thereby generating substantial social value. The study underscores the transformative potential of integrating technology with community engagement practices. The significance of this research lies in its contribution to understanding how inclusive, ethical, and collaborative TESI frameworks can strengthen community resilience and ensure long-term sustainability. The study provides insights for policymakers, practitioners, and researchers seeking to leverage technology for equitable and sustainable development outcomes worldwide.

**Keywords:** Technology-Enabled Social Innovation, Sustainable Community Development, Digital Transformation, Inclusive Development, Community Empowerment.

## 1. Introduction

In the current scenario the societies face multiple challenges, including rising inequality, environmental degradation, and limited access to essential services. Traditionally the community development approaches failed to address these complex, multidimensional problems. With the advent of advanced technologies and Technology-enabled social innovation (TESI) it offers a promising way that combines digital tools with social processes to create sustainable solutions. According to Cajaiba-Santana (2014), social innovation represents a set of unique practices designed to address societal challenges more effectively than available alternatives. When technology infiltrates such efforts, the potential for transformative impact increases substantially. TESI aligns with the principles of sustainable community development, which prioritize environmental stewardship, social well-being, and economic vitality. The advanced digital tools have the capability to increase access to services, promote transparency, and enable marginalized groups to participate in development processes (Bason, 2018). As social communities integrate technology into their daily life, TESI provides new opportunities for enhancing autonomy and inclusive growth. The paper explores TESI's conceptual foundations, mechanisms, applications across sectors, challenges, and future directions for sustainable community development.

Technology-enabled social innovation (TESI) represents this shift by leveraging tools such as artificial intelligence, mobile applications, blockchain, and the Internet of Things (IoT) to design and implement solutions that are both scalable and community-centered. This approach not only enhances efficiency but also promotes participation, inclusivity, and empowerment, thereby redefining the pathways to sustainable community development in the digital era.

The paper also underscores that technology-enabled social innovation has emerged as a powerful catalyst for sustainable community development by enhancing inclusivity and participatory governance. When aligned with local needs, cultural contexts, and ethical considerations, digital tools can maximize social impact, enhance service delivery, and empower marginalized communities. The paper calls for context-sensitive and people-centric approaches that bridge digital divides while ensuring long-term sustainability. Future research should focus on impact assessment frameworks, policy integration, and adaptive governance models to strengthen the role of technology as an enabler of equitable and sustainable community transformation.

## 2. Conceptual Foundations of Technology-Enabled Social Innovation

### *2.1. Social Innovation*

Social innovation focuses on developing new ideas and practices that improve societal well-being. Franz et al. (2012) suggests that social innovation emerges from collaborative processes involving government, civil society, academia, and local communities. Unlike traditional innovations linked to market efficiency, social innovation prioritizes collective benefit, inclusivity, and long-term sustainability (Howaldt & Schwarz, 2017). Most of the times it involves participatory approaches, understanding communities as co-creators of solutions rather than passive recipients.

### *2.2. Technology as a Catalyst for Social Innovation*

With the introduction of new and advanced technologies the reach and scale of social innovation has significantly expanded. It facilitates communication, enables data-driven decision-making, and reduces service delivery costs (Chatterjee et al., 2023). Digital tools also promote transparency, accountability, and real-time monitoring, all of which strengthen development outcomes. According to OECD (2020), digital transformation increases the capacity of organizations to provide services effectively and efficiently, particularly in underserved areas.

### *2.3. Sustainable Community Development*

Sustainable community development focusses on long-term social, environmental, and economic well-being. It requires inclusive governance, ecological responsibility, and economic stability. Technology aligns with these goals by enabling participatory planning, managing natural resources efficiently, and supporting economic diversification (Roy & Dey, 2021). Gurumurthy et al. (2019) argues that digital rights and equitable access to technology are pertinent for truly sustainable development.

## 3. Mechanisms and Technologies that enables Social Innovation

### *3.1. Enhancing Access to data and Services*

Limited access to reliable data remains a major barrier to development. Technology democratizes information by expanding access to health services, education, financial systems, and agriculture-related knowledge. Digital platforms enable telemedicine, online learning, and mobile-based consulting services, minimizing the geographical barriers faced by remote communities (Bennet & McWhorter, 2020). Chatterjee et al. (2023) emphasize that digital tools enhance decision-making by providing timely and context-specific information.

### *3.2. Strengthening Governance and Transparency*

Digital tools enhance institutional transparency and create trust within communities. New initiatives such as mobile complaint systems, public information dashboards, and blockchain-enabled recordkeeping minimizes the chances for corruption (Agarwal & Brison, 2021). Open-government data systems allow citizens to track budgets, monitor service delivery, and participate in governance processes, thus strengthening local accountability (Bason, 2018).

### *3.3. Increased Economic Empowerment*

Technology-enabled social innovation increases economic opportunities by connecting communities to new markets and skills. Digital microfinance systems, mobile money, and e-commerce platforms empower small entrepreneurs and rural populations (Prahalad, 2006). The success of mobile money in Kenya demonstrates how digital financial services can catalyze community-level economic transformation; M-Pesa's model significantly lowered transaction costs and increased financial inclusion (Jack & Suri, 2014).

### *3.4. Supporting Participatory Decision-Making*

Technology-enabled social innovation also promotes social inclusion by allowing citizens and the stakeholders to participate in development planning processes. Digital mapping tools, online consultation platforms, and participatory GIS systems allow citizens and stakeholders to prioritize, promote and monitor local development projects. Technology-enabled participatory governance strengthens community development and results in effective resource allocation.

### *3.5. Data-Driven Community Solutions*

Data plays a pivotal role in building community-specific interventions. IoT devices, satellite imaging, and community data hubs support evidence-based planning in water management, waste disposal, and environmental monitoring (Kang et al., 2020). Data-driven decision-making help policy makers and community groups to prioritize and identify key issues, target resources effectively and efficiently, and monitor and evaluate the impact of technological interventions.

### *3.6. Building Collaborative Networks*

Technology connects diverse stakeholders, nurturing cooperative networks that are essential for social innovation. Digital platforms enhances communication between governments, NGOs, private organizations, and citizens, enabling shared learning and co-created solutions (Fazal & Raza, 2022). This interconnectedness in the decision-making process between stakeholders and cooperative networks enhances the capacity to address complex social challenges.

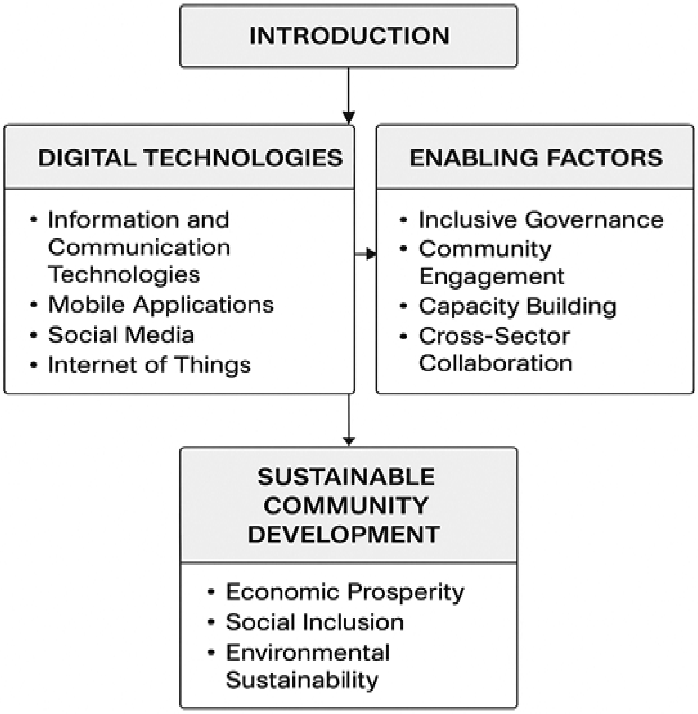


**Fig 1.** Technology enabled social innovation for sustainable community development (By Author)

## 4. Applications of TESI in Key Sectors

### *4.1. Education*

Technology such as IoT, artificial intelligence and machine learning has significantly expanded educational and skill enhancement access to the students through virtual classrooms, digital libraries, AI-supported personalized learning tools, and teacher training platforms. Murray et al. (2010) emphasize that educational innovations promote equity by reaching learners who are otherwise excluded due to geographical and economic barriers. Remote learning platforms in Indonesia and Africa illustrate how Technology-enabled social innovation supports continuity in education despite infrastructural limitations.

### *4.2. Healthcare*

Digital tools are reshaping healthcare delivery in communities lacking medical infrastructure. Telemedicine initiatives allow remote diagnosis and consultation, while Robotics , AI-assisted screening tools improve early detection of diseases (Schmidt & Cohen, 2013). Electronic health records facilitate continuity of care and enhance coordination among healthcare providers. UNDP (2022) notes that digital health ecosystems significantly improve health outcomes in developing countries by reducing service gaps.

### *4.3. Agriculture and Rural Development*

Smart agriculture tools like satellite-based weather forecasts, mobile-based crop advisory systems, IoT sensors for soil monitoring, and digital marketplaces provides farmers with better productivity and income. Kummitha (2019) argues that context-appropriate technological tools contribute to improved agricultural planning and rural wellbeing. Digital marketplaces enable small-scale farmers to sell products directly to consumers, increasing transparency and profits.

### *4.4. Environmental Sustainability*

Communities can monitor natural resources more effectively using IoT-based water sensors, GIS mapping, and remote sensing tools. Digital platforms also supports community waste management initiatives, for example the Brazilian cities are adopting mobile reporting systems to streamline waste collection. Kang et al. (2020) suggests that smart community technologies can significantly reduce ecological footprints while supporting sustainable urban development and building of smart cities.

### *4.5. Disaster Management*

Technology increases the adoption of proactive measures with respect to preparedness, response, and recovery in disaster-prone regions especially in hilly regions. Early warning systems, satellite imagery, and digital communication tools allow authorities to provide alerts quickly and mobilize community response. World Bank (2021) emphasizes that data-driven risk assessments significantly reduce casualties and resource losses.

### *4.6. Livelihoods and Entrepreneurship*

Technology-enabled social innovation supports digital entrepreneurship, offering training platforms, micro-enterprise apps, and online marketplaces. These digital tools expands and provide economic opportunities for youth, women, and marginalized groups. Digital business models enable microentrepreneurs to innovate and compete effectively in local and global markets (Afuah, 2018).

## 5. Enablers and Barriers

### *5.1. Digital Divide*

Unequal access to technology remains a significant barrier. Lack of internet connectivity in remote and hilly areas, digital skills, and affordable devices disproportionately affects rural areas, women, and marginalized groups (Bennet & McWhorter, 2020).

### *5.2. Digital Literacy*

Communities may struggle to use digital tools effectively as no proper training is provided to them. Without proper training, digital systems may increase inequalities rather than reducing them (Gurumurthy et al., 2019)

### *5.3. Privacy and Ethical issues*

Weak data protection measures put users at risk of exploitation, unethical practices or surveillance. World Bank (2021) stresses the need for ethical and rights-based data governance.

### *5.4. Infrastructure Challenges*

Poor infrastructure, particularly unreliable electricity and high-speed internet, limits the effectiveness of Technology-enabled social innovation initiatives in many developing countries (Agarwal & Brison, 2021).

### *5.5. Resistance to Change*

Cultural norms, fear of the unknown and fear of technology, and institutional inertia may hinder the adoption of innovative solutions (Franz et al., 2012). For smooth transition it is important for the government to take along all the stakeholders and citizens involved in the adoption of innovative solutions.

### *5.6. Financial Constraints*

Another challenge in sustaining Technology-enabled social innovation projects is inadequate funding, which is often difficult for local governments and community organizations to secure (Howaldt & Schwarz, 2017).

## 6. Future Directions and Opportunities

### *6.1. Integrating AI*

AI systems can effectively analyze the community data to identify important issues such as disease outbreaks, environmental threats, or social vulnerabilities (Schmidt & Cohen, 2013).

### *6.2. Strengthening Digital Infrastructure*

Digital identity systems, payment platforms, and public data systems helps in enabling the scalable innovation (UNDP, 2022).

### *6.3. Promoting Community Technology Hubs*

Local technology hubs can support digital training, innovation, and entrepreneurship skills to the local peoples (Fazal & Raza, 2022).

### *6.4. Encouraging Public-Private Partnerships (PPP mode)*

Collaboration across various sectors can mobilize resources, knowledge, and technology for social innovation (OECD, 2020).

### *6.5. Promoting Inclusive Innovation Ecosystems*

Ensuring that marginalized groups participate in designing digital solutions enhances the relevance and sustainability of innovations (Gurumurthy et al., 2019).

### *6.6. Global Social Innovations*

Globally successful social innovation models like mobile money or telemedicine can be adapted to new contexts through international cooperation (Kummitha, 2019).

## 7. Conclusion

Technology-enabled social innovation represents a transformative strategy for advancing sustainable community development. By leveraging digital tools to support education, healthcare, governance, agriculture, environmental sustainability, and entrepreneurship, TESI strengthens social resilience, promotes inclusivity, and enhances community well-being. While challenges such as digital divides, data privacy issues, and limited infrastructure remain, the potential for technology-driven social transformation is immense. When guided by participatory, ethical, and inclusive principles, TESI can build empowered, sustainable, and future-ready communities worldwide. Technology-enabled social innovation plays a critical role in advancing sustainable community development, when embedded within inclusive governance structures it can strengthen social capital, improve service effectiveness, and enable scalable solutions to persistent development challenges. However, the transformative potential of technology remains dependent upon ethical deployment, local capacity building, and collaboration. The findings of the study emphasize that sustainability is achieved not through technology alone, but through socially grounded innovation that integrates human-centered design, institutional support, and long-term impact orientation.

## References


- Afuah, A. (2018). *Business model innovation: Concepts, analysis, and cases.* Routledge.
- Agarwal, P., & Brison, J. (2021). Digital public infrastructure and inclusive development: Policy perspectives for emerging economies. *Journal of Development Policy and Practice, 6*(2), 145–162. https://doi.org/10.1177/2455133321999541
- Bason, C. (2018). *Leading public design: Discovering human-centered governance.* Policy Press.
- Bennet, D., & McWhorter, R. R. (2020). Digital literacy in underserved communities: Challenges and pathways for social inclusion. *Community Development Journal, 55*(3), 449–468. https://doi.org/10.1093/cdj/bsz032
- Cajaiba-Santana, G. (2014). Social innovation: Moving the field forward. A conceptual framework. *Technological Forecasting and Social Change, 82*, 42–51. https://doi.org/10.1016/j.techfore.2013.05.008
- Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2023). Digital transformation for sustainable development: A review and research agenda. *Information Systems Frontiers, 25*(2), 345–366. https://doi.org/10.1007/s10796-022-10326-0
- Fazal, S., & Raza, M. (2022). Technology for social good: A multidimensional framework for community development. *International Journal of Social Innovation Studies, 7*(1), 23–40.

- Franz, H. W., Hochgerner, J., & Howaldt, J. (2012). Challenge social innovation: An introduction. In H. W. Franz, J. Hochgerner, & J. Howaldt (Eds.), *Challenge social innovation* (pp. 1–16). Springer.
- Gurumurthy, A., Chami, N., & Bharthur, D. (2019). Digital justice: A rights-based approach to technology and social inclusion. *IT for Change Working Paper*. https://itforchange.net
- Howaldt, J., & Schwarz, M. (2017). *Social innovation and human development.* Edward Elgar.
- India Ministry of Electronics & IT. (2020). *Digital India: Empowering citizens through technology.* Government of India.
- Jack, W., & Suri, T. (2014). Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution. *American Economic Review, 104*(1), 183–223. https://doi.org/10.1257/aer.104.1.183
- Kang, J., Lee, H., & Kim, Y. (2020). Smart communities for sustainable urban development: An integrative model. *Sustainable Cities and Society, 52*, 101853. https://doi.org/10.1016/j.scs.2019.101853
- Kummitha, R. K. R. (2019). Smart technologies for community development: Lessons from Asia and Africa. *Technological Forecasting and Social Change, 148*, 119712. https://doi.org/10.1016/j.techfore.2019.119712
- Murray, R., Caulier-Grice, J., & Mulgan, G. (2010). *The open book of social innovation.* NESTA & The Young Foundation.
- OECD. (2020). *Digital transformation for sustainable development.* OECD Publishing.
- Prahalad, C. K. (2006). *The fortune at the bottom of the pyramid.* Wharton School Publishing.
- Roy, A., & Dey, B. (2021). Technology-enabled participatory governance for sustainable rural development. *Information Technology for Development, 27*(3), 580–602. https://doi.org/10.1080/02681102.2021.1872025
- Schmidt, J. P., & Cohen, J. (2013). *The new digital age: Reshaping the future of people, nations and business.* Knopf.
- UNDP. (2022). *Digital strategy 2022–2025: Reimagining development in the digital age.* United Nations Development Programme.
- World Bank. (2021). *World development report 2021: Data for better lives.* World Bank Publications.

Anusandhan: NDIM's Journal of Business and Management Research | ISSN No. 2581-8120, Vol. VIII, Issue 2, August 2026
http://doi.org/10.56411/anusandhan.2026.v8i1.16-25

# Unleashing the Potential of Artificial Intelligence in Human Resource Management

Isha Kataria (Corresponding Author)

Research Scholar, IMSAR
Maharshi Dayanand University
Rohtak, Haryana, India

Dr. Kavita Malik

Professor, UIET
Maharshi Dayanand University
Rohtak, Haryana, India.

**Isha Kataria, ORCID ID: 0009-0006-3483-4689**
**Dr. Kavita Malik, ORCID ID: 0009-0000-6688-0408**

**Date of receiving the manuscript: March 25, 2026** **Date of publication: August 31, 2026**

**Abstract:** The persistence of this study is to find out the impact of Artificial Intelligence on Human Resource Management in the current era of technology & how AI will affect HRM in future. The entire human resources industry is undergoing a transformative phase due to the impact of artificial intelligence to stand out among competitors; organizations must adopt and implement innovative HR practices. This study employs a scientific methodology to shed light on the advancements of artificial intelligence in the field of human resources. A multiple regression analysis is conducted to assess the influence of Artificial Intelligence on Human Resource Management practices. ANOVA test has been used to determine how well the independent factors in the model forecast the dependent variable. Findings suggest that factors like agreement on AI software for talent recruitment & familiarity with AI introduction have a significant and positive influence on HRM Practices. the "agreement of AI software assisting in finding the best talent for the job" & "familiarity with AI introduction" have sig values of 0.011 & 0.005 the values for the other two criteria related to AI usage "firms do not already use in the context of this analysis, the variables "AI-based HR software" and "use of proprietary or outside software" do not exhibit statistical significance, since their values exceed 0.05. All the criteria, except for "use of proprietary or outside software," have positive beta values. This research paper is original research paper and is not published anywhere.

**Keywords**: Artificial Intelligence, Human, Resources, Recruitment, Talent management, chatbots, Automation, Shortlisting, Talent Management, Employee Engagement, Screening, Applicant tracking

## 1. Introduction

The study of "intelligent agents" or device that could observe from its environment and take actions intended to increase the probability that it will succeed in achieving its goals, is what computer science represents as AI research. Artificial intelligence (AI) is defined by Kaplan and Haenlein as "the system's potential to properly infer the external input, to study from such data, and to apply such learnings to fulfil specified goals and tasks through flexible adaptation of technology. AI is a software which can think intelligently alike to how an intelligent human thinks, it consists of virtual assistant, talent acquisition, performance appraisal, learning and development. AI takes more repetitive tasks, high volume tasks, sourcing screening, assessing candidates, automating, matching candidates to the right job, helping to find a large pool of talented applicants for the recruiters. As an intelligent intermediary that "receive precepts from the environment and execute the actions accordingly," as defined by Russell and Norvig (2021) [14] Organizations across a wide range of sectors, including banking, retail, healthcare, and education, are gradually implementing AI to transform their business practices. As indicated by a 2017 survey from Tata Consultancy Services, AI's significant impact is most prominent in the IT sector. AI is the study, learning, and prediction based on data. It is well described as the machines which displays intelligence similar to that of human's mind (Russell & Norvig, 2021) [14]. In the realm of HR, AI facilitates smoother execution of traditional practices with increased efficiency. The adaptability of AI extends to incorporating diverse media forms like images, audio, and video, along with the potential for innovative training modules using game mechanisms to deliver personalized and creative content. AI software, relying on historical data analysis, offers insights and predictions. Algorithms, defined by scholars (Finn, 2017; Kearns & Roth, 2019; Lum & Chowdhury, 2021) [8], consist of rules guiding task execution. Companies need to identify the specific HR practices for AI integration, with various available AI software handling tasks like resume screening, applicant tracking, and candidate testing. AI enables the creation of intelligent machines capable of understanding and responding to their surroundings, encompassing ranges such as computer vision, speech processing/recognition, NLP, knowledge presentation.

## 2. Objectives of the study

- To investigate the impact of Artificial Intelligence on Human Resource Management.
- To study the Human Resource dimensions in which Artificial Intelligence (AI) finds its applications?

## 3. Literature Review

Jacob et al., (2023) the author asserts that within talent acquisition, leaders are exerting increased effort to guide applicants through the recruitment process. Consequently, the implementation of AI in talent acquisition and the introduction of video recruiting are identified as two pivotal advancements that alleviate challenges and expedite the hiring process. Prentice et al., (2023) examines the impact of AI-powered tools on both the behaviors and performance of the employees. It explores reciprocal relationship, studying how AI performance influences job engagement, services, and overall job performance. Dr. G Nancy Elizabeth (2021) focuses on Implication of AI for HR, the effect of AI in the post covid 19 world, also focused on How AI based chatbots resolve candidates and the queries of the employees and help in boarding, training, performance appraisal process.(Ahmed Arslan 2022) focus on collaboration and interaction of human worker and robots, both working as team members, they found an area of worker of fear of indulging with Artificial intelligence and highlighted the problem of trust building with HR and robots it was a conceptual paper thus too found out the toughest challenge for HRM that relates with this paper. Baldegger et al., (2020) examines the disparity between the promises and actual implementation of AI in Human Resource Management (HRM) and proposes potential strategies for program development. They emphasize the swift global integration of AI into daily activities, with 31% of survey participants acknowledging its presence in their HRM processes. vivek v. yawalkar (2019) focused on benefits like cold reduction, enhanced services, screening the candidates, scheduling the interviews, onboarding, chat box system, Automatic answering machine. AI in recruitment, screening and interview process tools like amy, clara are used to schedule interviews, working meetings, reduce administrative burden, selecting, reduce discrimination, increase efficiency, enrich workplace learning. Thomas & George, (2019) the study focuses on qualitative research and explains how AI is implemented into special HR skills and domains and impacted the organization as a whole. How the manual work has been redefined by AI capabilities, AI has revolutionized the skills acquisitions, performance evaluation, learning and improvement.

## 4. Research Gap

A number of studies have highlighted the significance of Al in HRM practices and its impact on HRM strategies, most of the evaluated papers only provide a conceptual understanding of Al in HRM based on secondary data. By comprehending the experience and perception of IT company employees on the adoption and use of Al in HRM practices, this research study seeks to close this gap. Based on earlier literature reviews, researchers discovered that while HRM of businesses has received increasing attention in the past, few studies has been carried out to determine significance, influence of the Al in HRM operations. Recruitment, hiring, on boarding, employee engagement, performance management, and training and development in conjunction with AI have received less study attention. Artificial intelligence (AI) has not been used to test many aspects of human resource management, and little research has been done on how Al affects HRM in IT firms. For this reason, it is crucial to investigate a variety of topics that clarify how Al is integrated with HRM practices.

## 5. AI in Recruitment

AI is essential to many HRM procedures Tambe et al., 2019) [5], but hiring is where it's most beneficial (Eubanks, 2018). It enlarges the pool of candidates, improves productivity and job tenancy, and cuts down on hiring times and the expenses (Black & van Esch, 2020) [4]. The business landscape has undergone a radical transformation, and the integration of technology into the business sector is a key factor for ensuring success. AI significantly contributes to business operations, especially in the IT sector, leveraging tools like the Applicant Tracking System (ATS). It uses artificial intelligence (AI) algorithms to tokenize keywords, evaluate job descriptions, and compare each candidate's profile to the requirements for the position in terms of credentials, experience, and abilities. Instead of dedicating hours to manually search LinkedIn job advertisements, AI automates the process, identifying top talent while allowing focus on other tasks. Additionally, the use of chatbots streamlines the review of applications, reducing the time spent on the hiring process. Chatbots act as a representative that caters to the candidates 24/7 thus increasing candidate engagement and reaching out to qualified candidates to inform them about their status and also to schedule an interview. With AI as an asset to the selection process any kind of discrimination (gender, age etc.) will be eliminated and decisions will be based on the skills/ merit.

## 6. Prescreening/ Pre Selection

The AI technique relies on the job description provided by the company and actively scans for potential job applicants. Professionals undergo prescreening through social media platforms like Facebook and LinkedIn. Additionally, screening is based on applications directly submitted to job postings. Some software also conducts prescreening by assessing applicants' personality traits. Selection procedures must provide the fairness to all applicants in order to evade unfavorable or unequal conclusions for individuals belonging to protected groups (Tippins et al., 2021) [15]. Personality tests are incorporated to assess whether candidates possess the requisite qualities and abilities necessary for the job.

## 7. AI & Training and Development

As per a research study conducted by Oracle, approximately 27% of HR leaders believe that AI-driven solutions for employee training will positively influence the learning and development of employees. AI is being used into employee training systems to improve automation, personalization, and professional and career development in general. AI not only enhances the quality of content, courses, scheduling, and delivery in employee training programs but also enables customization, providing users with a more personalized learning experience. The AI driven training process includes loading employee's chatbots and authentication data, virtual trainers use AI methods to monitor the progress of learners and also provide feedback and instruction.

The AI tool assesses employees' proficiency levels by analyzing continuous assessments conducted at the conclusion of each stage in the training program. AI-supported training aids in monitoring individual employee progress in real time, providing instantaneous data for immediate feedback. Integration of AI with an internal online learning system enables new hires to undergo simulation-based training post their initial training period, featuring interactive modules powered by AI. This approach allows employees to access training from any location and at any time, as companies can deliver training through websites, mobile apps, and similar platforms. Employee performance has improved dramatically once training programs switched to AI-based ones.

## 8. AI and Employee Engagement

Employee engagement encompasses clarity in roles, opportunities for learning, and recognition through rewards. Artificial Intelligence plays a vital role in establishing an unbiased and fact-based ongoing feedback system. Challenges commonly encountered during training, such as location, timing, and finding a suitable trainer, are overcome with AI-driven interactive training programs that employees can access at their convenience from any location. The use of talent acquisition software has significantly reduced the workload associated with the recruitment process, streamlining approximately 75% of the tasks involved.

The traditional recruitment process, involving job posting on relevant websites and candidate searches is time-consuming. AI platforms like LinkedIn, Glassdoor, indeed, and Naukri employ machine algorithms to offer job recommendations based on candidates' resumes, the keywords they use, their search history, and their network connections. AI facilitates more efficient and time-saving video or audio interviews through integrated software, aiding companies in the recruitment and selection process. Additionally, AI-integrated tools such as chatbots, Applicant Tracking Systems (ATS) and customer relationship management increase real-time communication to address candidate inquiries and deliver updates on their application status. AI is frequently used at different stages of the onboarding, recruitment, and the selection procedures.

## 9. AI and Talent Management

Talent management involves organizational planning aimed at fulfilling workforce requirements. Within this framework, HR engages in activities like talent acquisition, employee management, performance management, and succession planning. A system power-driven by artificial intelligence (AI) scrutinizes resumes, associating them to profiles of efficacious employees in equivalent roles. In India, AI has significant influence primarily in the realms of recruitment and the training and development functions within HR. Multinational companies like Ikea, loreal, Unilever, amazon now all used AI power-driven recruiting systems Such as Robo vera, Mya the chatbot, Hirevue assessments to expand their candidate acquisition techniques from changed jobs to abolish unqualified candidates.

In the book "Human resource management (HRM): theory, practices, and innovative approaches" By Dr. Davinder Sharma mentioned the online performance monitoring where performance metrics that is the performance appraisal that managers do, employees now have online access to actual performance data, with online data employees can self-monitor their progress and thus manage their own performance in 90% of the cases. Each employee possesses a personalized online learning and growth plan crafted to enable them to autonomously navigate their career. This ensures a continuous challenge and fosters ongoing development and growth in their role as an employee. They use expert software so the employees can self-manage most HR problems. IT Company Satyam has developed an interesting software for performance appraisal and performance tracking. Online PM led to less time consumption in reviewing the developmental needs of the company and uniformity and completeness in evaluating managing development of human capacity. All top recruitment companies in India such as Sutra HR, ABC consultants, Adecco India, Ikeya human capital, Kelly services India, and Manpower group India are implementing the AI system in the total process of recruitment and training. According to the Middle Consulting Group (2018) and Tippins et al. (2021) [15] there is a clear definition of the recruiting standards, which include the requirement to avoid workplace discrimination. However, there is a chance that the use of algorithms in the employment process will reinforce preexisting prejudices. Accordingly, HR via utilizing AI in the recruitment process, plays a critical role in fostering more inclusion. To predict an applicant's achievement on the job, data gathered via methods like social media, online tests, taped interviews, and CV screening is compared to industry standards set by the job analysis Derous & Ryan, 2019 [6]. There is a potential for data scientists to place greater trust in decisions guided by AI compared to decisions made by domain experts and this inclination may impact the considerations in the design process (Charlwood & Guenole, 2022) [7]. Data scientists may try to go forward with the top twenty percent of candidates after video interviews; however, industrial/organizational psychology would argue that this strategy might lead to too few candidates moving on to the next round of the selection cycle, Kelan (2023) [8]. Information gathered from various sources, including CV screening, online assessments, recorded interviews, or social media, undergoes assessment based on job analysis standards to predict the potential job performance of applicants Derous & Ryan, 2019 [12]. The reliability of AI-guided decisions in comparison to decisions made by experts in the field, as noted by Charlwood & Guenole (2022) [7], may impact the considerations in the design process. While data scientists may prioritize advancing top 20% of candidates after video interviews, a viewpoint from industrial/organizational psychology, as indicated by Kelan (2023) [10], might argue that this approach could lead to insufficient candidate numbers for the subsequent selection stage.

While there is a concern about the potential replacement of professions by AI and automation, it is essential not to overlook the vital role these technologies play in attracting, hiring, and retaining talent. In the current era of rapid change and shortages in digital skills, finding suitable personnel has become more challenging than ever. Basic artificial intelligence programs such as automated social media scraping tools and screening chatbots, can assist recruiters in sourcing and evaluating candidates. These tools are intended to provide rudimentary or below-average indications of a candidate's likelihood of success in the workplace. According to Society for the Human Resource Management, an example of such a chatbot is Mya, an AI recruitment assistant developed by First Job. Mya interacts with the candidates to ensure that they meet the required job criteria, addresses the particular inquiries,

and keeps them informed about the status of their applications every time. In instances where the bot cannot perform a task, it contacts individuals and offers 24/7 assistance through chat, SMS, Skype, or email. Developed in collaboration with its colleagues at Pymetrics, Unilever is one corporation that has used an effective artificial intelligence screening process. At present, in a thriving programme, questions are developed "obviously to elicit responses indicative of job success and perceive appropriate behaviors" in the context of a video interview. HireVue's artificial intelligence algorithm carefully examines with each candidate's responses, words, tone, and their emotional condition. Furthermore, to assist in assessing a candidate's emotional intelligence and genuineness, Affectiva has recently created emotion detecting software.

Tailored employee experiences: According to a study by IBM, AI can be effectively incorporated into a new hire's orientation program. New employees might face challenges in finding the right avenues for networking and in learning more about the company. Relying on conversations with nearby colleagues may not be sufficient, especially if the newcomer works in a different division. In their paper on transforming HR with AI, IBM executives stated, "To expedite the onboarding process for new hires, IBM is working on a system that will address their most crucial or job specific inquiries." Artificial intelligence system can offer recommendations for training or furnish details such as names, locations, and contact information of individuals the new employee must connect with during their early days. Moreover, AI engines might guide the employee by emphasizing the presence of valuable information on an enthusiastic webpage for new hires.

***H1:*** *HRM is significantly impacted by AI.*

## 10. Research Methodology

The study uses a mixture of qualitative and quantitative research approaches in its research methodology. Primary and secondary data were both used in the examination. Use of a structured questionnaire helped in the collection of the primary data. 200 individuals acknowledged the questionnaire. 170 fully completed questionnaires were utilized for the data analysis after the data's plausibility and reliability were taken into the account. Secondary data was gathered from the PDFs, journals, and articles. Logical conclusion was reached through the interpretation and analysis of the primary and secondary evidence. Data analysis was done using SPSS software. The questionnaire's internal consistency and reliability were assessed using the Cronbach's alpha. Multiple linear regression was used to examine the data. This analysis was carried out to ascertain whether artificial intelligence had a substantial impact on HRM and HR practices, as well as to assess how well the research model performed in this regard.

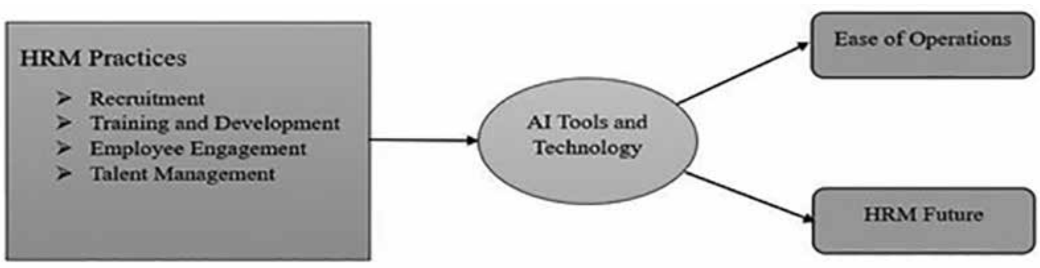


**Fig 1:** Conceptual Framework

*Source: Authors*

## 11. Data Analysis and Interpretation

***Reliability Analysis***

Cronbach's alpha is a statistical measure commonly used to assess the reliability or consistency of a set of survey or test items. An alpha value greater than 0.7 is generally considered acceptable for the internal consistency.

The Cronbach's alpha of 0.719 suggests that survey instrument has a good level of the internal consistency, meaning that the questions in questionnaire measures the same underlying construct or concept. This reinforces the reliability of the questionnaire for measuring sustainable HR practices. It's important to note that while Cronbach's alpha provides a useful measure of internal consistency, it does not guarantee the validity of the instrument. Validity refers to whether the questionnaire is measuring what it is intended to measure. Therefore, it's advisable to consider other forms of validity assessment in addition to internal consistency when evaluating the quality of a survey instrument. Overall, based on the information provided, it seems that the survey instrument has demonstrated good internal consistency, and the questions are effective in measuring the intended concept of sustainable HR practices.

**Table 1:** Reliability Analysis

| **Number of Items** | **Cronbach's Alpha** |
|---|---|
| 4 | .719 |

*Source*: Authors

## 12. Impact of AI on HRM Practices

A multiple regression analysis is conducted to assess the impact of Artificial Intelligence on Human Resource Management (HRM) practices. The R square value of 0.617 indicates that approximately 61.7% of the variability in the HRM practices can be explained by the independent variable, which in this case is the use of AI tools and technology.

The R square value is a measure of the goodness of fit of the regression model. In your context, it suggests that a significant portion of the variation in HRM practices can be attributed to the influence of artificial intelligence. A higher R square value generally indicates a better fit of the model to the data. However, it's important to note that while R square is a useful metric, it doesn't provide information about the direction or strength of individual predictors or the overall statistical significance of the model. In regression analysis, it is also advisable to examine the coefficients, p-values, and other relevant statistics to gain a more all-inclusive understanding of the relationships between variables. Artificial intelligence have a substantial impact on HRM practices, as indicated by the relatively high R square value. Further examination of the individual variables and statistical significance would contribute to a more thorough interpretation of the results.

**Table 2**: Model Summary

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | 0.752 | 0.617 | 0.513 | 0.98732 |

*Source*: Authors

**Table 3**: ANOVA

| | Model | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 22.573 | 4 | 5.31 | 5.055 | 0.007 |
| | Residual | 11.437 | 12 | 0.895 | | |
| | Total | 34.01 | 16 | | | |

*Source: Authors*

The results of the ANOVA test are displayed in the Table 3, which helps in determining how well the independent factors in this model forecast the dependent variable. Table 3 shows that the significance value is less than typical p value of 0.05, at 0.007. Thus, it demonstrates that the independent variables (tools and technologies related to artificial intelligence) used for this model are useful in identifying dependent variable, which is HRM Practices.

**Table 4:** Multiple Regression Output

| Model | Unstandardized coefficient | | Standardized coefficient | Sig. |
|---|---|---|---|---|
| | B | Std. Error | Beta | |
| (Constant) | 3.492 | 1.295 | | 0.021 |
| Training and Development | 0.259 | 0.278 | 0.183 | 0.342 |
| Recruitment | 0.923 | 0.261 | 0.591 | 0.005 |
| Employee Engagement | 0.832 | 0.498 | 0.314 | 0.008 |
| Talent Management | 0.785 | 0.273 | 0.524 | 0.01 |

*Source*: Authors

The information provided in Table 4 gives insights into the results of the regression analysis, specifically regarding significance & direction of the relationship between independent variables related to artificial intelligence and Human Resource Management practices. Significance values (sig values) for the independent variables are reported. It appears that the "agreement of AI software assisting in finding the best talent for the job" and "familiarity with AI introduction" have sig values of 0.011 and 0.005, respectively, both less than the standard significance value of 0.05. This suggests these two variables are statistically significant and have an influence on HRM practices. On other hand, the values for other two criteria related to AI usage ("firms do not already use in the context of this analysis, the variables "AI-based HR software" and "use of proprietary or outside software" do not exhibit statistical significance, since their values exceed 0.05. All the criteria, except for "use of proprietary or outside software," have positive beta values. Beta values represent the strength and direction of the relationship between independent and dependent variables. The positive beta values suggest a positive correlation, indicating that as the independent variables increase, HRM Practices also tend to increase. The findings suggest that factors like agreement on AI software for talent recruitment and familiarity with AI introduction have a significant and positive impact on HRM Practices. This implies that organizations where these factors are present are likely to have more favorable HRM practices. It's crucial to consider the practical significance of the results, the size of the coefficients, and potential confounding variables when interpreting regression results.

Based on the information provided, it seems that certain aspects of AI, such as agreement on its use for talent recruitment and familiarity with its introduction, are statistically significant and positively correlated with favorable HRM Practices. Further analysis and consideration of the context and potential limitations would deliver a more comprehensive understanding of the relationship.

As a result, the H0 (Null) hypothesis is rejected and the H1 (Alternate) hypothesis is supported, indicating that HRM is positively and largely impacted by Artificial Intelligence.

## 13. Conclusion

AI is emerging as an effective tool in the workplace of the future that is changing how HR functions. AI is assisting companies in creating more flexible, effective, and people-focused workplaces through anything from quicker pre-screening and better hiring to individualized training and ongoing growth. It increases access to talent by reaching a larger pool of applicants, expedites the recruiting process, lowers expenses, and enhances the hiring process as a whole. Candidates can be accurately matched based on qualifications, experience, and potential via intelligent systems that analyse job needs and identify critical talents. AI-driven chatbots increase engagement even more by responding to questions, assisting candidates, and setting up interviews with ease. AI is changing employee learning and development beyond recruiting. Virtual training assistants are able to track development, assess performance, and make real-time learning route recommendations. Interactive modules, simulation-based programs, and digital platforms that could be accessed at any time and from any location via websites or mobile apps are available for new hires to on-board. This fosters a culture of flexible learning where growth is ongoing rather than sporadic. These advancements are fundamentally made possible by machine learning, which analyses data patterns and makes well-informed predictions. Organizations can more successfully identify potential high performers by using data collected from resumes, evaluations, interviews, and professional profiles. AI will enhance HR by enabling HR professionals to concentrate more on empathy, strategy, innovation, and meaningful employee interactions as firm's transition to a more digital future.

## 14. Future Research

With an emphasis on hiring, talent management, training and development, and employee engagement, the research study observes the revolutionary effects of artificial intelligence (AI) on human resource management (HRM). The study acknowledges the rapid evolution of HRM practices from traditional methods to advanced approaches involving automation, augmented intelligence, robotics, and AI. The paper reviews existing literature to provide a wide-ranging overview of the current state of AI in HRM and highlights the challenges and opportunities connected with its implementation. With an emphasis on hiring, this study examines how AI is revolutionizing HRM, Talent management, training and development, and employee engagement. In the future, the researchers propose ways to ensure justice and mitigate biases in AI-driven HR practices. The researcher can explore the evolving skills set required for HR professionals in the Era of AI. The researchers can compare global trends In AI adoption with HR across different industries and regions by studying these sections the scholars and practitioners can explore the evolving landscape of AI in HRM.

**Conflict of Interest:** All authors declare that they have no conflicts of interest.

## References


- Artificial Intelligence in HRM Dr. G Nancy Elizabeth (2021) Quest Journals Journal of Research in Business and Management Volume 9 ~ Issue 7 (2021) pp: 40-42 ISSN(Online):2347-3002 www.questjournals.org.
- Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies A Arslan, C Cooper, Z Khan, I Golgeci, I Ali - International Journal of Manpower, 2022.
- AI-Driven Automation in Human Resource Management: Shaping the Future of Workforce Dynamics Ms. Isha Kataria & Dr. Kavita Malik Third Concept an International Journal of Ideas ISSN 0970-7247, Vol. 37 No. 444 FEBRUARY 2024.
- Black, Stewart & van Esch, Patrick. (2019). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons. 63. 10.1016/j.bushor.2019.12.001.
- Cappelli, Peter & Tambe, Prasanna & Yakubovich, Valery. (2018). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. SSRN Electronic Journal. 10.2139/ssrn.3263878. DOI:10.2139/ssrn.3263878.
- Charlwood, Andy & Guenole, Nigel. (2022). Can HR adapt to the paradoxes of artificial intelligence? Human Resource Management Journal. 32. 10.1111/1748-8583.12433. DOI:10.1111/1748-8583.12433.
- Empirical Economics Letters, 23 (Special Issue 3): (February 2024) ISSN 1681 8997 https://doi.org/10.5281/zenodo.11116679.
- https://www.technologyreview.com/2021/02/26/1020007/what-is-an-algorithm/.
- https://doi.org/10.1111/1748-8583.12433
- https://doi.org/10.1111/1748-8583.12511
- Prentice, Catherine & Wong, Ipkin & Lin, Z... (2023). Artificial intelligence as a boundary-crossing object for employee engagement and performance. Journal of Retailing and Consumer Services. 73. 103376. 10.1016/j.jretconser.2023.103376. DOI:10.1016/j.jretconser.2023.103376.
- Ryan, Ann & Derous, Eva. (2019). the Unrealized Potential of Technology in Selection Assessment. Journal of Work and Organizational Psychology. 35. 10.5093/jwop2019a10. DOI:10.5093/jwop2019a10.
- Rico, Baldegger & Caon, Maurizio & Sadiku, Kreshnik. (2020). Correlation between Entrepreneurship Orientation and Implementation of AI in Human Resources Management (HRM). Technology Innovation Management Review. 10. 72-79. 10.22215/timreview/1348. DOI:10.22215/timreview/1348.
- S.J., RUSSEL & Norvig, Peter. (2003). Artificial Intelligence - A Modern Approach. Prentice Hall Inc., New Jersey.
- Tippins, Nancy & Oswald, Frederick & McPhail, S. (2021). Scientific, Legal, and Ethical Concerns About AI-Based Personnel Selection Tools: A Call to Action. Personnel Assessment and Decisions. 7. 10.25035/pad.2021.02.001. DOI:10.25035/pad.2021.02.001.

Anusandhan: NDIM's Journal of Business and Management Research | ISSN No. 2581-8120, Vol. VIII, Issue 2, August 2026

http://doi.org/10.56411/anusandhan.2026.v8i1.26-37

# Attachment Styles and Reflective Functioning as Predictors of Emotion Regulation and Management among Indian Youth

Deepanshi Garg

B.Sc. Clinical Psychology (Hons with Research)
Amity Institute of Psychology & Allied Psychology
Amity University, Noida, UP

Dr. Mamata Mahapatra

Professor
Centre Head for Organisational Psychology
Amity Institute of Psychology & Allied Psychology
Amity University Uttar Pradesh
Noida, UP

**Deepanshi Garg, ORCID ID: 0009-0007-3889-2701**
**Dr. Mamata Mahapatra, ORCID ID: 0000-0001-6350-6007**

**Date of receiving the manuscript: April 16, 2026** **Date of publication: August 31, 2026**

**Abstract:** Emotional regulation plays an important role in how young adults understand, express, and manage their emotions in everyday life. The ability to regulate emotions flexibly becomes especially important during youth, as individuals navigate academic, social, and interpersonal challenges. Attachment styles and reflective functioning may influence this process by shaping how individuals understand their own and others' mental states. Though the existing literature is replete with findings on attachment style and emotion regulation, the influence of reflective functioning on emotion regulation flexibility remains largely unexplored, especially in the context of Indian young adults. Therefore, the present study seeks to explore the relationship among attachment style, reflective functioning, and emotion regulation flexibility among Indian young adults. A quantitative correlational research design was used with a sample of 206 Indian college students aged 18 to 25 years by having them complete the ECR-S scale, RFQ scale and the FREE scale. The findings indicated a positive association of attachment anxiety with uncertainty in reflective functioning. Reflective functioning uncertainty was negatively associated with emotion regulation flexibility. Regression analysis further indicated that reflective functioning dimensions, namely uncertainty and certainty, significantly predicted emotion regulation flexibility, whereas attachment anxiety and avoidance did not directly predict it. The study highlights the importance of reflective functioning in understanding emotional adaptability among young adults and suggests that enhancing mentalization may support better emotional regulation flexibility.

**Keywords:** Reflective functioning, attachment styles, emotion regulation flexibility, mentalization, Indian young adults.

# 1. Introduction

People experience emotional states which affect their thinking, actions and their ability to connect with others. The adaptive functions of emotions enable people to recognize essential personal information which helps them deal with environmental obstacles (Gross, 1998). According to Gross (1998) emotion regulation describes the techniques people use to control their emotional experience and expression. People who can manage their emotions effectively experience better mental health results while people who struggle with emotion management develop psychological disorders that include anxiety and depression and problems with social relationships (Hoeksema et al., 2010). Understanding the mechanisms which underlie adaptive emotional regulation represents a major research focus in the field of psychology.

## *1.1* Attachment Styles

Attachment theory, proposed by Bowlby, forms the core construct to study the emotional development and relationship patterns of individuals (Bowlby, 1969,1982). At the core level, attachment can be described as the innate biological construct through which the infant is compelled to seek the proximity of the caregiver for safety and protection during times of stress and anxiety. This evolutionary construct leads to the formation of cognitive-affective schemas referred to as internal working models, which include the individual's expectations regarding their lovability and the dependability of others. Attachment patterns become significant for the creation and maintenance of interpersonal relationships during the adulthood (Mikulincer & Shaver, 2016).

There are four main styles of attachment, as proposed by the dimensional approach that combines the two factors of anxiety (fear of rejection) and avoidance (discomfort with dependence) (Bartholomew & Horowitz, 1991). The four major styles of attachment stem from the sensitive caregiver experiences (Alidoosti et al., Tang 2024). Insecure attachment relationships make up 40-50% of the population and cause different forms of psychopathology (Ghannam, 2022).

## *1.2* Reflective Functioning

People develop their ability to understand mental states through the process of mentalization which deals with both self-attribution and attribution to others (Fonagy et al., 2016). RF operates on a continuum which ranges from prementalizing to the ability to establish trust in understanding complex intentionality. Secure early attachments establish RF development pathways through their ability to reflect back to the child what they need while enabling self-regulation through caregiver-based emotional connection (Sirparantha et al., 2024). Insecure attachments lead to RF impairment because avoidant styles result in under-mentalizing while ambivalent styles create over-mentalizing (e.g., excessive suspicion; Henry et al., 2022). Emerging adults depend on RF as a bridge between their attachment relationships and their ability to experience social interactions because it supports their development of empathy and reciprocal relationships (Ghannam, 2022). Low RF serves as the clinical foundation for personality disorders which include borderline pathology because attachment trauma interferes with mental state discussions (Katherine et al., 2021).

## *1.3 Emotion Regulation Flexibility and Management*

Emotion regulation flexibility refers to the adaptive capacity to select and regulate appropriate strategies: interpersonal (e.g., reassurance seeking, sharing) or intrapersonal (e.g., cognitive reappraisal, suppression) in response to stressors, rather than relying on maladaptive strategies (Kafetsios et al., 2024; Mosannenzadeh et al., 2024). Unlike difficulties with inflexible emotion regulation, ERF helps to build resilience through the establishment of balance between hypo-regulation (under-control), hyper-regulation (over-control), or balanced regulation; further, secure attachment predicts ERF (Girme et al., 2021; Tang, 2024). Conversely, insecure forms of attachment constrain ERF; for instance, attachment anxiety predicts inflexible interpersonal strategies and expressive suppression, while avoidance predicts an over-reliance on intrapersonal suppression and reappraisal suppression (Arora, 2025; Waffa & Pitigala, 2024).

The attachment relationship establishes a triadic connection which affects the regulatory function of an individual and this function then impacts their emotion regulation function. Secure attachment enables individuals to develop their regulatory function which allows them to control their emotions in an adaptable manner while building their capacity to withstand challenges. The insecure attachment creates obstacles which result in inflexible behavior and difficulties in forming connections with others (Alidoosti et al., 2024).

***Objectives***

- To study the relationship between attachment anxiety, attachment avoidance and emotion regulation flexibility.
- To study the relationship between reflective functioning and emotion regulation flexibility.
- To study the predictive role of attachment styles and reflective functioning in emotion regulation flexibility.

## 2. Review of Literature

Aydin and Arslan (2026) examined the effect of attachment styles and automatic thoughts on emotion regulation among early adolescents. In their study, 320 middle-school students aged 10-14 years were taken into account. Aydin and Arslan utilized the Scales of Attachment Styles, Automatic Thoughts, and Emotion Regulation for conducting their analysis by Pearson Correlation and Multiple Regression. Their findings show that secure attachment had positive impact on cognitive reappraisal, and anxious/ambivalent attachment predicted emotional suppression positively. No evidence of avoidant attachment being a predictor for reappraisal and suppression was provided by their findings. They also found a correlation between high levels of negative automatic thoughts and low cognitive reappraisal and high emotional suppression.

Brumariu et al. (2026) studied the relationship between early adolescents' attachment security, parental emotion socialisation, and regulation of positive emotions. The study included 112 early adolescents, including 55 boys, who completed an attachment interview and rated their own regulation of positive emotions through savouring and dampening, along with their parents' emotion socialisation strategies. The findings showed that adolescents who were more securely attached to both mothers and fathers used more savouring and less dampening of positive emotions. The study also found that parents' savouring and dampening strategies were associated with similar emotion regulation patterns in children. These findings suggest that both attachment security and parental emotional responses play an important role in shaping how adolescents understand and regulate positive emotional experiences.

This paper examines the role of vulnerable attachment as a risk factor for depression and stress, using emotion regulation and coping as mediators, carried out by Koçak Özel and Yalçınkaya Alkar (2026). In the current study, the participants comprised 282 university students who were sampled via the use of convenience sampling method. The measures used to collect the information include self-report questionnaires such as Vulnerable Attachment Style Questionnaire, Experiences in Close Relationships Inventory-II, Emotion Regulation Questionnaire, Ways of Coping Inventory, Perceived Stress Questionnaire, and Beck Depression Inventory. The results indicated that emotion regulation and coping skills acted as mediators in the associations between vulnerable attachment, depression, and stress. From the current study, ambivalent and anxious-dependent attachment were found to have association with depression and stress symptoms. Also, ambivalent attached individuals were found to have more ineffective and less effective coping styles that increase vulnerability to depression and stress.

Arora (2025) studied the impact of anxiety and avoidance attachment style on emotional regulation and coping strategies among young adults in the age range 19-25 years. Results identify the positive relationship between attachment anxiety and cognitive reappraisal and expressive suppression coping strategy and reveal a tendency towards emotion-oriented and avoidant coping. Contrary to the above finding, however, the relationship between attachment avoidance and expressive suppression is positively correlated whereas the relationship between attachment avoidance and cognitive reappraisal is negatively correlated.

Alidoosti et al. (2024) conducted a study on the moderating effect of reflective functioning in the connection between attachment styles and emotion regulation problems using a non-experimental and correlational study approach. Inferences made from the research indicate that individuals with secure attachment possess high confidence and good emotion regulation compared to anxious-avoidant individuals who experience emotion regulation difficulties and have high uncertainty.

Mosannenzadeh et al. (2024) explored the connection between the attachment insecurity and the degree of flexibility of using the interpersonal vs. intrapersonal strategies of emotion regulation (ER) in the face of stressful events within romantic relationships. This research emphasizes the fact that adult attachment insecurity is associated with emotion regulation problems in romantic relationships. In particular, it indicates the importance of an inflexible and dependent use of intrapersonal or interpersonal ER strategies (e.g., suppression, seeking reassurance, or sharing).

Tang (2024) conducted a literature review to compile the effects of attachment styles on psychological resilience and emotion regulation. Through the numerous studies, the paper demonstrates how early relationships affect resilience later in life and how individuals regulate their emotions. The paper incorporates concepts from developmental, clinical, and social-personality psychology. The literature review concludes that attachment is significant to flexibility and regulation of emotions, as people with secure attachment styles are more resilient and better at regulating their emotions.

The study carried out by Enriquez et al. (2024) explored the association between emotion regulation and mentalization as well as how mentalization is connected to interpersonal problems. The findings suggest that the employment of emotion regulation techniques that entail emotions is connected to why mentalization has been found to be related to interpersonal problems, especially those that are involved in avoiding others. There is also an indication that the involvement of emotion regulation techniques that entail emotions may overly rely on mentalization, thus worsening interpersonal problems among adolescents.

Waffa and Pitigala (2024) conducted research emphasizing on how adult attachment styles stem from caregiver interactions in the childhood and how it influences the emotional regulation and management in native Sri Lankan population. They used 147 participants and the ECR-SV to measure the style of attachment and the ERQ to test the regulation of emotions. They found that both anxious and avoidant attachment style predict reduced cognitive reappraisal, but the anxious style has a greater effect than the avoidant style. Both aspects of adult styles of attachment were linked with increased levels of emotional suppression, but avoidance was more significant than anxiety. This study showed that insecure adult attachment style interferes with the positive processing of emotions and increases the likelihood of the negative processing of emotions among Sri Lankan youth.

Ghannam (2022) examined the relationship between attachment styles, mentalization ability, and the ability of emerging adults to get along with others. 77 emerging adults participated in the study by answering questions about their mentalization ability, attachment style, and interpersonal functioning. The results revealed a strong relationship between mentalization ability and two-way communication styles. Attachment styles were also found to have a good connection with interpersonal functioning. In addition to this, the findings of the study reveal the importance of attachment styles and the ability of emerging adults to be emotionally aware. Adding to which, these factors contribute to the opening up of intimate relations with others.

Henry et al. (2022) investigated the relationship between attachment and mentalizing in emerging adults. The authors found out that avoidant and ambivalent attachment styles are related to under- and over-mentalizing. The study consisted of 69 emerging adults (34 females, 35 males; ages between 18-29 years, mean being 21.72 years, SD being 2.26). It was found by the authors that avoidant and ambivalent attachment types are associated with under- and over-mentalization. Insecure attachment styles' participants did worse on MASC than those with secure attachment style. It was found by the authors that avoidant people demonstrated higher degree of under-mentalization than people in secure attachment group.

### *Research Gap and Rationale*

The connection between attachment and general emotion regulation has been established through previous research but research has not yet examined how reflective functioning supports flexible emotion regulation. The studies which investigated how RF functions as a mediator between attachment styles and emotional regulation abilities across different contexts (Mikulincer & Shaver, 2016; Bonanno & Burton, 2013) represent a limited research area. The mechanism needs to be understood because it serves as the foundation for developing interventions which will increase emotional flexibility and resilience among young adults who face academic and social stress.

The current study approaches the gap by examining how attachment patterns influence emotion regulation flexibility which reflective functioning serves as a potential mediating mechanism. The study investigates these relationships through Indian college students because this group represents a cultural context that shows different attachment and emotional regulation patterns from Western countries.

### *Hypothesis*

H1: Attachment anxiety will be negatively associated with emotion regulation flexibility.

H2: Attachment avoidance will be negatively associated with emotion regulation flexibility.

H3: Reflective functioning will be positively associated with emotion regulation flexibility.

H4: Attachment styles and reflective functioning will significantly predict emotion regulation flexibility.

## 3. Research Methodology

### *3.1 Research Design*

This study utilized a quantitative correlational research design. Such design was applied to investigate the association between attachment style, reflective functioning, and emotion regulation flexibility in the sample of young adults. Moreover, the objective of the study included investigating whether attachment styles and reflective functioning predicted emotion regulation flexibility.

### *3.2 Sample*

The sample composed of 206 individuals (young adults) who were aged between 18 and 25 years. Most of the participants were students in colleges and universities. There were 75 male participants in the sample group, accounting for 36.4% of total sample, while 131 participants were female, i.e., 63.6% of total sample.

Inclusion criteria required that the participants had to be between18 and 25 years of age, enrolled in any college or university, and willing to give their informed consent to participate in the study.

### *3.3 Sampling Technique*

The participants were randomly chosen for the study using random sampling. The selection process involved choosing the young adults who belonged to the target population, met the inclusion criteria, and were ready to take part in the study.

### *3.4 Tools Used*

#### RFQ- 8 item

Reflective functioning was assessed through the use of the 8-item Reflective Functioning Questionnaire by Fonagy et al. (2016). Reflective functioning is measured using the concept of mentalization. Mentalization involves understanding one's and other people's mental states. There are two subscales in this test: certainty in mental states and uncertainty in mental states.

The scores for the two subscales were computed based on the guidelines in the manual. Higher scores in the certainty subscale suggest more certainty in understanding mental states, whereas high scores in the uncertainty subscale suggest uncertainty in understanding mental states.

#### ECR-S

For the purposes of measuring attachment style, Experiences in Close Relationship–Short Form was used. This scale was created by Wei, Russell, Mallinckrodt, and Vogel in 2007. This scale consists of 12 questions and measures the following two types of attachment: attachment anxiety and attachment avoidance.

Questions are rated according to the 7-point Likert scale, where 1 stands for strong disagreement and 7 for strong agreement. Four items are reverse-coded as described in the manual. The scale has proved to be reliable and valid.

#### FREE Scale

Flexibility of emotion regulation was evaluated through the use of Flexible Regulation of Emotional Expression Scale created by Burton and Bonanno in 2016. This scale contains 16 questions that evaluate how well a person can increase or restrain emotions depending on the situation.

Both components of the scale: enhancement and suppression were evaluated independently, and then summed up to receive the result.

### *3.5 Procedure of Data Collection*

A total of 206 young adults ranging in age from 18 to 25 years participated in this study. Before conducting the experiment, the reason for doing this study was clearly stated to all participants. All participants signed informed consents. They were also assured that all answers would be kept confidential for research purposes only.

After establishing rapport and providing necessary instructions, participants completed the questionnaires measuring reflective functioning, attachment styles, and emotion regulation flexibility. The collected responses were then scored according to the respective scale manuals.

### *3.6 Statistical Analysis*

Data analyses were carried out using IBM SPSS version 21. Descriptive statistics comprising mean and standard deviation were used in order to describe the data. The Pearson correlation coefficient was used in order to examine the association between attachment anxiety, attachment avoidance, reflective functioning certainty, reflective functioning uncertainty, and emotion regulation flexibility.

Moreover, multiple regression analyses were conducted in order to determine the prediction of the aforementioned variables on emotion regulation flexibility in young adulthood.

## 4. Results

**Table 4.1.** Mean and Standard Deviation for the variables of the study

| Variable | M | SD | N |
|---|---|---|---|
| Emotion Regulation Flexibility | 56.69 | 14.84 | 206 |
| Attachment Anxiety | 24.46 | 7.06 | 206 |
| Attachment Avoidance | 17.42 | 6.14 | 206 |
| Uncertainty (RFQ_U) | 7.12 | 4.65 | 206 |
| Certainty (RFQ_C) | 1.95 | 1.39 | 206 |

Mean and Standard deviation for emotion regulation flexibility, attachment anxiety and avoidance, uncertainty and certainty in reflective functioning was calculated. Participants reported a mean score of 56.69 (SD = 14.84) on emotion regulation flexibility, indicating moderate variability in individuals' ability to regulate emotions flexibly. Attachment anxiety had a mean of 24.46 (SD = 7.06), while attachment avoidance showed a mean of 17.42 (SD = 6.14), suggesting variability in attachment-related dimensions within the sample. With respect to reflective functioning, the mean score for uncertainty (RFQ_U) was 7.12 (SD = 4.65), indicating a moderate level of uncertainty in understanding mental states. In contrast, reflective functioning certainty (RFQ_C) was relatively low, with a mean of 1.95 (SD = 1.39), suggesting generally lower levels of certainty about mental states among participants.

**Table 4.2**- Bivariate correlations for the variables of the study.

| Variable | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1. Attachment Anxiety | — | | | | |
| 2. Attachment Avoidance | .20** | — | | | |
| 3. Emotion Regulation Flexibility | −.08 | −.04 | — | | |
| 4. Uncertainty (RFQ_U) | .38** | .05 | −.19** | — | |
| 5. Certainty (RFQ_C) | −.10 | −.01 | −.10 | −.26** | — |

** Correlation is significant at the 0.01 level.

Product–moment correlations were carried out in order to assess the association between attachment anxiety, attachment avoidance, reflective functioning (uncertainty and certainty), and emotion regulation flexibility. Attachment anxiety was found to have a positive correlation with attachment avoidance, r (204) = .20, p = .004, as well as with reflective functioning uncertainty, r (204) = .38, p < .001. However, there was no statistically significant correlation of attachment anxiety with emotion regulation flexibility, r (204) = −.08, p = .261, or reflective functioning certainty, r (204) = −.10, p = .174.

Attachment avoidance was not significantly associated with emotion regulation flexibility, *r*(204) = −.04, *p* = .567, reflective functioning uncertainty, *r*(204) = .05, *p* = .476, or reflective functioning certainty, *r*(204) = −.01, *p* = .849. Emotion regulation flexibility was negatively correlated with reflective functioning uncertainty, *r*(204) = −.19, *p* = .007, indicating that greater uncertainty was associated with lower flexibility. Its correlation with reflective functioning certainty was not significant, *r*(204) = −.10, *p* = .169. Finally, reflective functioning uncertainty and certainty were moderately and negatively correlated, *r*(204) = −.26, *p* < .001.

**Table 4.3.** Hierarchical Multiple Regression Predicting Emotion Regulation Flexibility

| Predictor | B | SE | β | t | p |
|---|---|---|---|---|---|
| **Step 1** | | | | | |
| Constant | 61.53 | 4.37 | — | 14.07 | < .001 |
| Attachment Anxiety | −0.16 | 0.15 | −.07 | −1.03 | .304 |
| Attachment Avoidance | −0.06 | 0.17 | −.03 | −0.35 | .724 |
| **Step 2** | | | | | |
| Constant | 66.37 | 4.68 | — | 14.18 | < .001 |
| Attachment Anxiety | −0.00 | 0.16 | .00 | −0.00 | .997 |
| Attachment Avoidance | −0.07 | 0.17 | −.03 | −0.44 | .660 |
| Uncertainty (RFQ_U) | −0.72 | 0.24 | −.23 | −2.96 | .003 |
| Certainty (RFQ_C) | −1.66 | 0.75 | −.16 | −2.20 | .029 |

**Note.** N = 206. *B* = unstandardized regression coefficient; *SE* = standard error of the coefficient; *β* = standardized coefficient. Step 1: $R^2 = .007$, Adjusted $R^2 = -.003$. Step 2: $R^2 = .059$, Adjusted $R^2 = .040$. $\Delta R^2 = .052$ for Step 2 ($p = .005$).

The current study used the Hierarchical Multiple Regression to investigate the ability of attachment anxiety, attachment avoidance, and reflective functioning (uncertainty and certainty) to predict emotion regulation flexibility. In step one, the variables of attachment anxiety and attachment avoidance were entered as the independent variables. The result was not statistically significant, with F (2, 203)=0.69, p=.501, accounting for 0.7% of the variance in emotion regulation flexibility ($R^2$=0.007, Adjusted $R^2$=-0.003).

Reflective functioning variables of uncertainty and certainty were entered into the regression equation in Step 2. The regression model was statistically significant, F (4, 201) = 3.13, p = .016, accounting for 5.9% of the variance in emotion regulation flexibility ($R^2$ = .059, Adjusted $R^2$ = .040). The addition of reflective functioning variables was highly significant in the regression model, $\Delta R^2$ = .052, F Change (2, 201) = 5.54, p = .0

In the final model, attachment anxiety ($B = -0.00$, $SE = 0.16$, $\beta = .00$, $p = .997$) and attachment avoidance ($B = -0.07$, $SE = 0.17$, $\beta = -.03$, $p = .660$) were not significant predictors. However, reflective functioning uncertainty ($B = -0.72$, $SE = 0.24$, $\beta = -.23$, $p = .003$) and reflective functioning certainty ($B = -1.66$, $SE = 0.75$, $\beta = -.16$, $p = .029$) were significant negative predictors of emotion regulation flexibility.

## 5. Discussion

The study investigated the interrelationships between attachment styles (anxiety and avoidance), reflective functioning (RF), which included certainty (RFQ-C) and uncertainty (RFQ-U), and emotion regulation flexibility (ERF), which was measured using the FREE scale, in 206 Indian college students. This study is embedded in the conceptual model in which RFQ is considered to be a contributing factor in the association between attachment and ERF. Descriptively, the study revealed moderate levels of attachment insecurity in the form of anxiety (M = 24.46, SD = 7.06) and avoidance (M = 17.42, SD = 6.14), and high levels of RFQ uncertainty (M = 7.12, SD = 4.65) in comparison to RFQ certainty (M = 1.95, SD = 1.39), and ERF (M = 56.69, SD = 14.84). These findings are in line with the non-clinical profiles of emerging adults, which are characterized by moderate levels of insecurity and lower levels of mentalization and RF, which are considered to be the norm in the face of relational transitions (Ghannam, 2022; Henry et al., 2022). Both bivariate and multivariate analyses offered partial support to the study hypotheses, highlighting the salience of RF over attachment in the prediction of ERF.

## 6. Conclusion

The current research explored the association between attachment style, reflective functioning, and emotion regulation flexibility in young Indian adults. The results revealed that attachment anxiety is related to uncertainty in reflective functioning. On the other hand, attachment anxiety and attachment avoidance were not found to be direct predictors of emotion regulation flexibility.

Reflective function was found to be a strong predictor of the flexibility of emotion regulation. This means that understanding one's mental states and those of other people is important for the flexibility of emotion regulation. Generally, reflective function emerged as a crucial element of the improvement of emotional adaptability in young adults.

### *6.1 Theoretical Implications*

The study adds to the existing literature through demonstrating that reflective function might have more predictive power than attachment style when it comes to emotion regulation flexibility. This finding confirms the assumption that there is more to emotion regulation than attachment patterns, with one's capacity for mental state understanding playing an important role.

The results may form the groundwork for future studies aimed at investigating the effect of reflective functioning to be a potential mediator between attachment style and flexibility in emotion regulation.

### *6.2 Managerial and Practical Implications*

The findings can be useful for colleges, universities, counselling centres, and youth mental health programmes. Since reflective functioning was linked with emotion regulation flexibility, institutions can include activities that improve self-reflection, emotional awareness, and perspective-taking among students.

Counsellors and mental health professionals can also focus on strengthening reflective functioning through reflective journaling, guided discussion, emotional awareness exercises, and mentalization-based approaches. This may help young adults manage stress, relationships, and emotional challenges more effectively.

### *6.3 Limitations*

A cross-sectional approach was applied in this study; hence, there could not be any causation between variables examined. Self-reports may have posed a problem of response bias. Also, the study only involved college students between the ages of 18 and 25 that reduced the generalization of findings.

### *6.4 Future Scope*

Future studies can use longitudinal or experimental designs to understand causal relationships more clearly. Reflective functioning can also be studied as a mediator between attachment styles and emotion regulation flexibility. Further research may include larger and more diverse samples from different regions of India and may consider other variables such as resilience, coping styles, self-esteem, and psychological distress.

## References


- Alidoosti, M., Hosseini, S. M., & Namazi, A. (2024). Moderating role of reflective functioning in the relationship between attachment styles and emotion regulation difficulties. *Journal of Psychological Processes*, *12*(11), 125–142.
- Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist*, *55*(5), 469–480. https://doi.org/10.1037/0003-066X.55.5.469
- Arora, S. (2025). Effect of early anxiety and avoidance attachment styles on emotional regulation and coping styles in young adults. *International Journal of Behavioral Sciences*, *2*(2), 1–17. https://doi.org/10.37745/ijbsc.2025
- Aydin, O., & Arslan, Ü. (2026). Investigating attachment styles and automatic thoughts on emotion regulation in early adolescence. *Mehmet Akif Ersoy University Journal of Education Faculty, 77*, 86–101. https://doi.org/10.21764/maeuefd.1825842
- Bartholomew, K., & Horowitz, L. M. (1991). Attachment styles among young adults: A test of a four-category model. *Journal of Personality and Social Psychology*, *61*(2), 226–244. https://doi.org/10.1037/0022-3514.61.2.226
- Bonanno, G. A., & Burton, C. L. (2013). Regulatory flexibility: An individual differences perspective on coping and emotion regulation. *Perspectives on Psychological Science*, *8*(6), 591–612. https://doi.org/10.1177/1745691613504116

- Bowlby, J. (1982). *Attachment and loss: Vol. 1. Attachment* (2nd ed.). Basic Books. (Original work published 1969)
- Brennan, K. A., Clark, C. L., & Shaver, P. R. (1998). Self-report measurement of adult attachment: An integrative overview. In J. A. Simpson & W. S. Rholes (Eds.), *Attachment theory and close relationships* (pp. 46–76). Guilford Press.
- Brumariu, L. E., Nair, T. K., Bogdan, A. G., Waslin, S. M., Muntean, A., & Kerns, K. A. (2026). Early adolescents' attachment security, parental emotion socialisation, and early adolescents' emotion regulation of positive emotions. *Cognition and Emotion*, 1–8. https://doi.org/10.1080/02699931.2025.2612606
- Burton, C. L., & Bonanno, G. A. (2016). The Flexible Regulation of Emotional Expression scale (FREE): Development and validation among undergraduates and community adults. *Psychological Assessment*, *28*(9), 1070–1083. https://doi.org/10.1037/pas0000244
- Enriquez, M., Pérez, A., & García, L. (2024). Relationship between emotion regulation and mentalization. *PsyArXiv*. https://doi.org/10.31234/osf.io/65squ
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, *5*(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11
- Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.
- Fonagy, P., Luyten, P., Moulton-Perkins, A., Lee, Y. W., Warren, F., Howard, R., et al. (2016). Development and validation of a self-report measure of mentalizing: The Reflective Functioning Questionnaire. *PLoS ONE*, *11*(7), Article e0158678. https://doi.org/10.1371/journal.pone.0158678
- Ghannam, R. (2022). Relationship between attachment styles, mentalization ability, and interpersonal functioning in emerging adults. *Journal of Adult Development*, *29*(3), 210–225.
- Girme, Y. U., Sng, A. A., & Rodriguez, L. M. (2021). Does infant attachment security predict adult emotion regulation strategies in relationship-threatening situations? *Journal of Social and Personal Relationships*, *38*(10), 2952–2975. https://doi.org/10.1177/02654075211040500
- Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271
- Henry, J., Mayes, L., & Luyten, P. (2022). Attachment and mentalizing in emerging adults. *Mentalization and Attachment Studies*, *14*(2), 88–104.
- Kafetsios, K., Rantala, A., & Kokkinou, E. (2024). Influence of attachment insecurity on emotion regulation strategies. *BMC Psychology*, *12*(277). https://doi.org/10.1186/s40359-024-01686-w
- Katherine, S., Steel, C., & Luyten, P. (2021). Professional carers' attachment style and reflective functioning: Links with adolescent behavioral and emotional adaptation in residential care. *Children and Youth Services Review*, *126*, Article 106044. https://doi.org/10.1016/j.childyouth.2021.106044
- Koçak Özel, T., & Yalçınkaya Alkar, Ö. (2026). The vulnerable attachment style as a predictor of depression and stress: The mediating role of emotion regulation and coping strategies. *Journal of Clinical Psychology Research, 10*(2), 154–167. https://doi.org/10.57127/kpd.26024438.1681669
- Mikulincer, M., & Shaver, P. R. (2016). *Attachment in adulthood: Structure, dynamics, and change* (2nd ed.). Guilford Press.
- Mosannenzadeh, F., Luijten, M., MacIejewski, D. F., Wiewel, G. V., & Karremans, J. C. (2024). Adult attachment and emotion regulation flexibility in romantic relationships. *Behavioral Sciences*, *14*(9), 758. https://doi.org/10.3390/bs14090758
- Sirparanta, A. E., Miljkovitch, R., Zdebik, M. A., Pascuzzo, K., Garon-Bissonnette, J., & Moss, E. (2024). Links between early and concurrent attachment and reflective functioning in young adulthood. *Developmental Psychology*, *61*(5), 843–856. https://doi.org/10.1037/dev0001790

- Tang, X. (2024). The effects of attachment styles on resilience and emotion regulation. *Journal of Education, Humanities and Social Sciences*, *26*, 755–759. https://doi.org/10.54097/shp3g660
- Waffa, F. R., & Pitigala, K. (2024). How attachment styles influence emotional regulation of young adults in Sri Lanka. *British Journal of Multidisciplinary and Advanced Studies: Health and Medical Sciences*, *5*(1), 57–92. https://doi.org/10.37745/bjmas.2022.0436
- Wei, M., Russell, D. W., Mallinckrodt, B., & Vogel, D. L. (2007). The Experiences in Close Relationships Scale short form (ECR-S): The development of a self-report instrument for assessing relationship-specific anxious attachment. *Journal of Counseling Psychology*, *54*(1), 17–29. https://doi.org/10.1037/0022-0167.54.1.17

Anusandhan: NDIM's Journal of Business and Management Research | ISSN No. 2581-8120, Vol. VIII, Issue 2, August 2026

http://doi.org/10.56411/anusandhan.2026.v8i1.38-46

# Behavioural Biases and Pension Investment Decisions: Evidence from Employees in Kerala

Sajitha S M

Research Scholar,
Department of Commerce,
Govt. College foe Women, University of Kerala, Thiruvananthapuram.

Dr. Nimi Dev R

Associate Professor, Department of Commerce,
Govt. College foe Women, University of Kerala Thiruvananthapuram.

**Sajitha S M, ORCID ID: 0009-0009-5097-0930**
**Dr. Nimi Dev R, ORCID ID : 0000 0002 3738 4912**

**Date of receiving the manuscript: April 28, 2026** **Date of publication: August 31, 2026**

**Abstract:** Pension investment decisions are often influenced by psychological tendencies rather than purely rational financial reasoning. This study examines the role of five key behavioural biases overconfidence, loss aversion, present bias, anchoring, and herding in shaping pension investment behaviour among employees in Kerala. Using a structured questionnaire and responses from 100 participants, the study employs descriptive statistics and correlation analysis used to analyse the relationship between these biases and pension investment behaviour, including contribution levels, plan participation, and fund selection. The findings reveal that all five behavioural biases overconfidence, loss aversion, present bias, anchoring, and herding are significantly present among employees in Kerala with respect to pension investment decisions. However, among individual predictors, present bias showed a significant negative impact on pension investment behaviour, while overconfidence, loss aversion, anchoring, and herding biases were not significant. The results further reveal a significant variation in the strength of behavioural biases, with overconfidence and herding emerging as the most dominant factors influencing pension investment decisions among employees in Kerala.

**Keywords:** Pension Investment, Behavioural Biases, Employees

## 1. Introduction

Pension investment decisions are essential for long-term financial security, yet individuals often deviate from rational financial behaviour due to psychological and emotional factors. Behavioural finance explains that biases such as overconfidence, loss aversion, present bias, anchoring, and herding influence investment choices, risk-taking, and retirement savings behaviour (Kahneman & Tversky, 1979; Thaler, 1999). These biases significantly affect pension planning and long-term financial well-being (Lusardi & Mitchell, 2014; Pompian, 2012).

In India, particularly in Kerala, behavioural factors continue to influence pension investment decisions despite relatively high literacy and financial awareness levels. Studies show that biases such as herding and anchoring affect individuals' allocation between safe and risky investments (Verma & Verma, 2018; Szakadatova, Caplanova, & Sivak, 2025). Understanding these behavioural tendencies can help policymakers and financial institutions design effective financial literacy programs and retirement planning strategies.

Although retirement planning has gained importance in India, limited studies have examined behavioural biases in pension investment decisions among employees in Kerala. This study addresses the gap by analysing the impact of overconfidence, loss aversion, present bias, anchoring bias, and herding behaviour on pension investment behaviour among employees enrolled in schemes such as the National Pension System (NPS) and Employees' Provident Fund (EPF). Using statistical tools such as one-sample t-test and multiple regression analysis, the study finds that behavioural biases significantly exist among employees, while present bias has a statistically significant negative impact on pension investment behaviour.

## 2. Review of Literature

Szakadatova, Caplanova, and Sivak (2025) reviewed studies on behavioural biases and personality traits affecting pension investment decisions, highlighting the influence of status quo bias, loss aversion, default effects, and Big Five personality traits on pension choices. Maheshwari, Samantaray, Panigrahi, and Jena (2024) found that financial literacy indirectly improves investment decisions through positive attitude and overconfidence. Maheshwari, Samantaray, and Jena (2023) identified overconfidence, herding, loss aversion, anchoring, and disposition effect as major behavioural biases influencing investors. Goyal, Gupta, and Yadav (2023) reported that financial literacy, risk perception, and social influence significantly affect herding behaviour and heuristic-driven investment decisions among Indian millennials. Bihari, Dash, Kar, Muduli, Kumar, and Luthra (2022) reviewed behavioural finance literature and confirmed the significant role of cognitive and emotional biases in investment decision-making. Jain, Walia, and Gupta (2020) found herding, loss aversion, and overconfidence to be the most influential biases among equity investors. Trönnberg and Hemlin (2019) showed that pension investment decisions are shaped by both analytical reasoning and behavioural biases, including sunk-cost effects. Weiss-Cohen, Ayton, Clacher, and Thoma (2019) highlighted the impact of framing, naïve diversification, projection bias, and cognitive overload on pension trustees' decisions. Verma and Verma (2018) found evidence of disposition effects in pension fund asset allocation but no support for the house-money effect. Bizzotto (2017/2018) emphasized that behavioural biases such as present bias and overconfidence affect retirement decisions and argued that effective pension communication can help mitigate these biases.

## 3. Research Gap

Although behavioral finance research has shown that psychological biases influence investment decisions, few studies have examined their impact specifically on pension investment behavior in India. Most existing studies focus on single biases, general savings, or national-level data, ignoring regional variations and the combined effect of multiple biases. Kerala, with its unique socio-economic and cultural context, may exhibit different patterns in retirement planning, but empirical evidence from this region is scarce. Additionally, previous research rarely links behavioral biases directly to measurable pension outcomes such as contribution levels, fund selection, and participation. There is also limited insight into how these biases can inform policy, employer interventions, or financial awareness programs. This study addresses these gaps by examining the combined effect of five key behavioral biases on pension investment decisions among employees in Kerala.

## 4. Statement of the Problem

Traditional economic theories assume that individuals make rational financial decisions, but behavioural finance shows that psychological biases often influence investment behaviour (Kahneman & Tversky, 1979; Barber & Odean, 2001). Biases such as overconfidence, loss aversion, present bias, anchoring, and herding can affect pension investment decisions and retirement planning (Benartzi & Thaler, 2007; Sahi et al., 2013). Despite their importance, limited research has examined these biases in the context of pension investments among employees in Kerala. Therefore, this study investigates the impact of selected behavioural biases on pension investment decisions to better understand factors affecting long-term financial security.

## 5. Significance of the Study

This study contributes to behavioural finance by providing region-specific evidence on how behavioural biases influence pension investment decisions among employees in Kerala. Unlike previous studies that mainly focused on general investment behaviour, it examines multiple behavioural biases simultaneously in the context of pension planning. The findings can assist policymakers, employers, and financial advisors in developing effective awareness programmes and behavioural interventions to encourage informed pension decisions. The study also enriches the understanding of behavioural determinants in retirement finance and offers a foundation for future research.

## 6. Objectives of the Study

- To identify the major behavioural biases (overconfidence, loss aversion, present bias, anchoring, herding) influencing pension investment decisions among employees in Kerala.
- To analyse the relationship between behavioural biases and pension investment behaviour (contribution level, fund selection, participation).
- To assess the relative strength of behavioural biases influencing pension investment decisions among employees in Kerala.

## 7. Hypotheses of the Study

- Behavioural biases do not significantly exist among employees in Kerala in pension investment decisions.

- Behavioural biases have no significant impact on pension investment behaviour.
- There is no significant difference in the strength of behavioural biases influencing pension investment decisions among employees in Kerala.

## 8. Scope of the Study

This study examines in what way behavioural biases such as overconfidence, loss aversion, present bias, anchoring, and herding influence the pension investment decisions of employees in Kerala. It concentrates on employees from both public and private sectors who participate in or are eligible for pension schemes like EPF and NPS. The study uses a structured questionnaire and SPSS-based statistical analysis to identify relationships between these biases and investment behaviour. The findings aim to provide insights for improving financial decision-making and retirement planning among Keralite employees.

## 9. Research Methodology

The study employs a quantitative and descriptive research design to examine the influence of behavioural biases on pension investment decisions among public and private sector employees in Kerala. A sample of 100 respondents enrolled in or eligible for pension schemes such as EPF and NPS will be selected through convenience sampling. Primary data will be collected using a structured questionnaire, while secondary data will be gathered from journals, books, reports, and government publications. Data analysis will be conducted using SPSS with descriptive statistics, correlation, and regression techniques to assess the relationship between behavioural biases and pension investment decisions.

## 10. Various Biases

### Data Anlysis and Interpretation

Profile of Sample

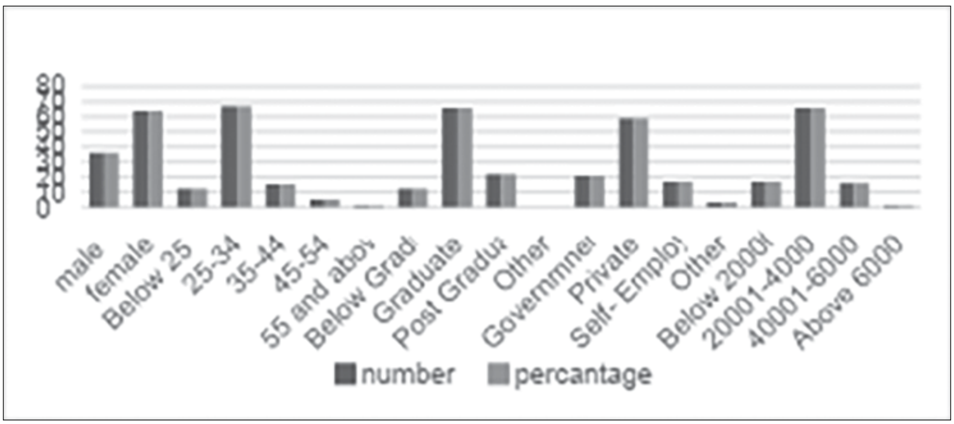


**Figure 1:** Profile of samples

*Source*: Primary data

Out of the 100 samples taken, most of the banking and fintech customers are female customers (64%). Most of them (67%) fall within the 25-34 years age group, with a graduation educational qualification (66%). Most (66%) of the population has an average monthly income of between Rs. 20001- 40000 and most (59%) of them were private employers

## Hypothesis – I

Ho- Behavioural biases do not significantly exist among employees in Kerala in pension investment decisions.

**Table 1.** One- Sample T Test Results

| Variable | Test Value | Mean | SD | T | df | Sig. (2-tailed) | Mean Difference | 95% Confidence Interval |
|---|---|---|---|---|---|---|---|---|
| Overconfidence (OC) | 3 | 4.00 | 0.487 | 20.53 | 99 | 0.000 | 1.00 | 0.90 – 1.10 |
| Loss aversion (LA) | 3 | 3.8125 | 0.598 | 13.58 | 99 | 0.000 | 0.8125 | 0.69 – 0.93 |
| Present bias (PB) | 3 | 3.82 | 0.677 | 12.11 | 99 | 0.000 | 0.82 | 0.69 – 0.95 |
| Anchoring bias (AB) | 3 | 3.835 | 0.646 | 12.93 | 99 | 0.000 | 0.835 | 0.71 – 0.96 |
| Herding behavior (HBe) | 3 | 3.8425 | 0.646 | 13.04 | 99 | 0.000 | 0.8425 | 0.71 – 0.97 |

level of significance: 0.05 and Test Value fixed to be 3

*Source*: Calculated values from primary data using IBM SPSS Statistic 25 software

A one-sample t-test was conducted to examine the presence of behavioral biases among employees in Kerala regarding pension investment decisions. The results showed that all measured biases—overconfidence ($M = 4.00$, $t(99) = 20.53$, $p < .001$), loss aversion ($M = 3.81$, $t(99) = 13.58$, $p < .001$), present bias ($M = 3.82$, $t(99) = 12.11$, $p < .001$), anchoring ($M = 3.83$, $t(99) = 12.93$, $p < .001$), and herding ($M = 3.84$, $t(99) = 13.04$, $p < .001$)—were significantly higher than the neutral value of 3. Therefore, the null hypothesis that behavioral biases do not exist among employees was rejected, indicating that these biases significantly influence pension investment decisions.

## Hypothesis – II

Ho- Behavioural biases have no significant impact on pension investment behaviour.

**Table 2.** Multiple Regression Analysis of Behavioural Biases on Pension Investment Behaviour

| Predictor Variables | B | Std. Error | Beta | t-value | Sig. (p) |
|---|---|---|---|---|---|
| Constant | 1.666 | 0.209 | – | 7.974 | 0.000 |
| Overconfidence Bias (OC) | 0.087 | 0.063 | 0.175 | 1.376 | 0.172 |
| Loss Aversion (LA) | 0.103 | 0.067 | 0.254 | 1.531 | 0.129 |
| Present Bias (PB) | -0.128 | 0.054 | -0.356 | -2.365 | **0.020*** |
| Anchoring Bias (AB) | -0.071 | 0.069 | -0.189 | -1.034 | 0.304 |

| **Predictor Variables** | **B** | **Std. Error** | **Beta** | **t-value** | **Sig. (p)** |
|---|---|---|---|---|---|
| Herding Behaviour (HB) | 0.094 | 0.064 | 0.250 | 1.454 | 0.149 |

*Source*: Calculated values from primary data using IBM SPSS Statistic 25 software

Dependent Variable: Pension Investment Behaviour, R = 0.325, $R^2 = 0.106$, Adjusted $R^2 = 0.058$, F-value = 2.218, Sig. (F) = 0.059, Sample Size (N) = 100, *$p < 0.05$ (statistically significant)

The multiple regression analysis examined the impact of overconfidence, loss aversion, present bias, anchoring bias, and herding behaviour on pension investment behaviour among employees. The model explained 10.6% of the variance in pension investment behaviour ($R^2 = 0.106$), while the adjusted $R^2$ value of 0.058 indicated modest explanatory strength. The overall model was marginally significant (F = 2.218, p = 0.059), showing that behavioural biases collectively have a weak but notable influence on pension investment behaviour.

Among the predictors, present bias was the only statistically significant factor ($\beta = -0.356$, p = 0.020), indicating that individuals who prioritise present consumption are less likely to engage in effective pension investment behaviour. Overconfidence bias, loss aversion, anchoring bias, and herding behaviour showed no statistically significant impact, as their p-values exceeded the 0.05 level.

The findings suggest that while several behavioural biases exist among employees, present bias plays the most important role in influencing pension investment decisions. This highlights the importance of behavioural factors, particularly time-related biases, in retirement planning and financial education programmes.

## Hypothesis – III

There is no significant difference in the strength of behavioural biases influencing pension investment decisions among employees in Kerala.

The descriptive statistics show that all five behavioural biases have relatively high mean values (Table 1), indicating that behavioural factors significantly influence pension investment decisions among employees in Kerala. Overconfidence bias recorded the highest mean score, followed by herding bias, anchoring bias, present bias, and loss aversion bias. These findings reflect employees' tendency to rely on personal confidence, peer influence, initial information, short-term preferences, and loss avoidance in pension-related decisions.

The study reveals that behavioural biases differ in their influence on pension investment behaviour, with overconfidence bias emerging as the most dominant factor, followed by herding behaviour. Present bias and anchoring bias showed moderate influence, while loss aversion was comparatively less dominant but still relevant.

Overall, the findings indicate that pension investment decisions are not purely rational but are strongly shaped by behavioural biases. The dominance of overconfidence and herding behaviour highlights the need for greater financial awareness and structured guidance to support informed and independent pension decision-making among employees.

**Table 4:** Friedman Test Results for Behavioural Biases

| Test | N | $\chi^2$ | df | p-value |
|---|---|---|---|---|
| Friedman Test | 100 | 13.189 | 4 | 0.010 |

*Source*: Calculated values from primary data using IBM SPSS Statistic 25 software

The Friedman test was conducted to examine whether there are significant differences in the relative strength of behavioural biases influencing pension investment decisions among employees in Kerala**.**The Friedman test results indicate a statistically significant difference in the strength of behavioural biases influencing pension investment decisions ($p < 0.05$). Hence, the null hypothesis is rejected.

This confirms that behavioural biases differ significantly in their relative influence on pension investment decisions among employees in Kerala. The dominance of overconfidence and herding biases suggests that both self-perceived financial competence and social influence play a crucial role in shaping pension investment behaviour.

## 11. Findings

- The one-sample t-test results reveal that all five behavioural biases—overconfidence, loss aversion, present bias, anchoring, and herding—are significantly present among employees in Kerala with respect to pension investment decisions.
- Herding, anchoring, present bias, and loss aversion were also found to be significantly prevalent, confirming that employees' pension decisions are influenced by peers, past reference points, present-oriented preferences, and fear of losses.
- The multiple regression analysis shows that behavioural biases together explain only 10.6% of the variation in pension investment behaviour, indicating weak explanatory power.
- The overall regression model was found to be statistically insignificant at the 5% level ($p = 0.059$), leading to the acceptance of the second null hypothesis that behavioural biases do not have a significant overall impact on pension investment behaviour.
- Overconfidence bias emerged as the most dominant behavioural factor, indicating that employees tend to overestimate their financial knowledge and decision-making ability.
- Herding bias was the second most influential bias, suggesting that pension investment decisions are strongly affected by peer behaviour and social influence.
- Present bias and anchoring bias showed moderate influence, reflecting short-term orientation and reliance on initial information or reference points while making pension-related decisions.
- Loss aversion, though comparatively less dominant, remains a relevant factor, highlighting employees' preference for safety and avoidance of potential losses in pension investments.

## 12. Suggestions

- Automatic pension contribution features such as auto-debit and default escalation should be strengthened to encourage regular retirement savings.
- Employers should conduct retirement planning and awareness programs to reduce delays in pension contributions.
- Employees should seek professional financial advice instead of relying only on personal judgment in pension investment decisions.

- Financial institutions should design simple and transparent pension products to reduce confusion and decision delays.
- Pension schemes with capital protection and minimum return guarantees should be promoted to address loss aversion.
- Employees should be educated to make independent pension decisions rather than depending on peers or reference information.
- Government agencies like Pension Fund Regulatory and Development Authority should strengthen digital reminders and personalised retirement planning tools.
- Greater focus should be given to younger employees to reduce present bias and improve retirement preparedness.
- Regular digital pension portfolio reviews should be encouraged to help employees monitor and adjust investments.
- Financial literacy programs should include behavioural finance concepts to help employees recognize and manage behavioural biases.

## 13. Conclusion

Behavioural finance suggests that pension investment decisions are often influenced by psychological biases rather than purely rational judgement (Kahneman & Tversky, 1979; Thaler, 1999). Biases such as overconfidence, loss aversion, anchoring, herding, and present bias affect retirement saving and investment behaviour (Pompian, 2012; Lusardi & Mitchell, 2014). This study found that all selected behavioural biases were prevalent among employees in Kerala. However, only present bias showed a significant negative impact on pension investment behaviour, indicating that employees who prioritise immediate financial needs are less likely to engage in effective retirement planning.

## References


- Barber, B. M., & Odean, T. (2001). *Boys will be boys: Gender, overconfidence, and common stock investment. The Quarterly Journal of Economics, 116*(1), 261–292. https://doi.org/10.1162/003355301556400
- Benartzi, S., & Thaler, R. H. (2007). *Heuristics and biases in retirement savings behavior. Journal of Economic Perspectives, 21*(3), 81–104. https://doi.org/10.1257/jep.21.3.81
- Bhushan, P., & Medury, Y. (2013). *Financial literacy and its determinants. International Journal of Engineering, Business and Enterprise Applications, 4*(2), 155–160.
- Bihari, A., Dash, M., Kar, S. K., Muduli, K., Kumar, A., & Luthra, S. (2022). *Exploring behavioural bias affecting investment decision-making: A network cluster-based conceptual analysis for future research*. International Journal of Industrial Engineering and Operations Management, *4*(1/2), 19–43.
- Bikhchandani, S., & Sharma, S. (2001). *Herd behavior in financial markets.* IMF Staff Papers, 47(3), 279–310
- Bizzotto, E. (2017/2018). *Pension funds and behavioural finance: Analysis of pension communication strategies in relation to the role of biases in retirement decisions* (Master's thesis). Università Ca'

Foscari Venezia. https://hdl.handle.net/20.500.14247/20839

- Chitra, K., & Sreedevi, V. R. (2014). *Does personality traits influence the choice of investment? Journal of Behavioral Finance, 15*(1), 57–65.
- Goyal, P., Gupta, P., & Yadav, V. (2023). *Antecedents to heuristics: Decoding the role of herding and prospect theory for Indian millennial investors*. Review of Behavioural Finance, *15*(1), 79–102.
- Jain, J., Walia, N., & Gupta, S. (2020). *Evaluation of behavioural biases affecting investment decision- making of individual equity investors by fuzzy analytic hierarchy process*. Review of Behavioural Finance, *12*(3), 297–314.
- Kahneman, D., & Tversky, A. (1979). *Prospect theory: An analysis of decision under risk. Econometrica, 47*(2), 263–292. https://doi.org/10.2307/1914185
- Kaustia, M., Alho, E., & Puttonen, V. (2008). *How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates.* Financial Management, 37(3), 391–411.
- Laibson, D. (1997). *Golden eggs and hyperbolic discounting*. Quarterly Journal of Economics, 112(2), 443–478. https://doi.org/10.1162/003355397555253
- Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5
- Maheshwari, H., Samantaray, A. K., & Jena, J. R. (2023). *Unravelling behavioural biases in individual and institutional investors investment decision-making: Intersection of bibliometric and systematic literature review*. South Asian Journal of Business and Management Cases, *12*(3), 275–299. https://doi.org/10.1177/22779779231210915
- Maheshwari, H., Samantaray, A. K., Panigrahi, R. R., & Jena, L. K. (2024). *Financial literacy in predicting investment decisions: Do attitude and overconfidence influence?*
- International Journal of Social Economics, *52*(2), 220–235. https://doi.org/10.1108/IJSE-05-2023-0370
- O'Donoghue, T., & Rabin, M. (1999). *Doing it now or later.* American Economic Review, 89(1), 103–124.
- Pompian, M. M. (2012). *Behavioral finance and investor types: Managing behavior to make better investment decisions.* John Wiley & Sons.
- Sahi, S. K., Arora, A. P., & Dhameja, N. (2013). *An exploratory inquiry into the psychological biases in financial investment behavior. Journal of Behavioral Finance, 14*(2), 94–103. https://doi.org/10.1080/15427560.2013.790387
- Sewell, M. (2010). *Behavioral finance.* University of Cambridge Working Paper.
- Szakadatova, E., Caplanova, A., & Sivak, R. (2025). Behavioral factors and pension investment decisions: Evidence from Central Europe. *Journal of Behavioral and Experimental Finance, 37*, 101976. https://doi.org/10.1016/j.jbef.2025.10197
- Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making, 12*(3), 183–206. https://doi.org/10.1002/(SICI)1099-0771(199909)12:3
- Trönnberg, C.-C., & Hemlin, S. (2019). Challenging investment decision-making in pension funds. *Qualitative Research in Financial Markets, 14*(2), 229–246. https://doi.org/10.1108/QRFM-03-2018-0039
- Verma, R., & Verma, P. (2018). Behavioral biases and retirement assets allocation of corporate pension plans. *Review of Behavioral Finance, 10*(4), 353–369. https://doi.org/10.1108/RBF-01-2017- 0009
- versky, A., & Kahneman, D. (1974). *Judgment under uncertainty: Heuristics and biases*. Science, 185(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124
- Weiss-Cohen, L., Ayton, P., Clacher, I., & Thoma, V. (2019). Behavioral biases in pension fund trustees' decision-making. *Review of Behavioral Finance, 11*(2), 128-143. https://doi.org/10.1108/RBF-05-2018-0049

http://doi.org/10.56411/anusandhan.2026.v8i1.47-58

# Dynamic Spillovers between Cryptocurrencies and BRICS Equity Markets: A TVP-VAR Analysis

Garima Anand, Bharti (Corresponding author), Ashish Kumar

University School of Management Studies,
Guru Gobind Singh Indraprastha University,
Dwarka, New Delhi, India,

**Garima Anand, ORCID ID: 0009-0009-2422-4133**
**Bharti, ORCID ID : 0000-0001-9626-9212**
**Ashish Kumar, ORCID ID : 0000-0002-4476-3494**

**Date of receiving of manuscript 29-06-2026** **Date of Publication 31-08-2026**

**Abstract:** With the rapid rise of cryptocurrencies and their growing impact on the global financial market, this paper examines dynamic return spillovers between cryptocurrencies and the equity market by employing Time-Varying Parameter VAR (TVP-VAR) approach. Using the data from February 26, 2018, to May 16, 2025, the results revealed cryptocurrencies as net transmitter and equity markets as receivers. Ethereum acted as prominent transmitter with Indian equity market being the most vulnerable. In order to strengthen the findings, the sample period was divided into three phases- pre-COVID-19, during COVID-19, and post-COVID-19. The results corresponding to the pandemic indicate heightened uncertainty with total connectedness surging to 72.72%. Remarkably, during COVID-19, Chinse equity market emerges as net recipient. Overall, findings challenge the popular belief that cryptocurrencies act as effective hedging instruments against equity market risks and highlight the growing vulnerability of emerging equity markets to crypto-driven volatility. This study has vital implications for practitioners and researchers.

**Keywords:** BRICS, Cryptocurrencies, Emerging Economies, TVP-VAR

## 1. Introduction

Over the last few decades, globalization and liberalization have reshaped global financial markets, fostering exceptional levels of integration between economies, financial systems and asset classes. This integration has led to spillovers across various asset classes including equities, bonds, commodities and foreign exchange markets. Among these assets, cryptocurrencies have emerged as new yet highly volatile assets by providing an additional channel for cross-market interdependencies. The market capitalization of cryptocurrencies reached USD 3.10 trillion by beginning of 2026, approximately four times the value in 2022 (Coin Market Cap). Cryptocurrencies have increasingly been utilized in regulated trading platforms, institutional investment strategies, exchange traded funds, and payment systems (Zhang *et al.*, 2025). They have evolved into mainstream financial instruments, creating opportunities across different domains. On the flip side, the rising integration has led to complexity, raising concerns on market fragility. Their interaction with other financial markets, especially equity, has made the ecosystem vulnerable to contagions and shocks (Balcilar *et al*., 2022). Furthermore, the spillovers intensify during crisis periods when disruptions in businesses trigger uncertainty through panic trading, herding behaviour, and the contagions across markets.

The relationship becomes more important in emerging economies due to the relatively weak financial system of these economies, increased debt burdens, limited fiscal space, and reliance on external financing (Alana *et al*., 2020). Among the emerging economies, Brazil, Russia, India, China, and South Africa (BRICS) economies are key contexts influencing the world of trade and investment flows, as they represent almost a half of the world population, and approximately 40% of the global GDP (Sindhu *et al*., 2025). Additionally, these nations rank prominently in cryptocurrency adoption, with India leading the Global Crypto Adoption Index. Consequently, studying the crypto-equity interlinkages in the context of BRICS for understanding market vulnerabilities and suggesting policy implications for effective risk management mechanisms is pertinent.

The extant studies examine crypto-equity linkages from the perspective of developed markets (Ahmed *et al*., 2023; Uzonwanne, 2021), documenting the existence of spillovers with varying intensity and direction of transmission. However, research on emerging markets is fragmented and inconclusive (Diaconaşu *et al*., 2023; El Hajj and Farran, 2024). For instance, Ustaoğlu (2022) reported a unidirectional spillover from Turkish equity to cryptocurrency market, whereas Sindhu *et al*. (2025) presented role reversal of spillover direction from crypto to BRICS equity markets. Contrarily, Joseph *et al*. (2024) found weak spillover between cryptocurrency and African equity markets.

Against this, the study investigates the return spillover between cryptocurrency-equity nexus, focusing on both the magnitude and direction of transmission. Furthermore, we seek to investigate return transmission patterns during COVID-19 pandemic between four significant cryptocurrencies, including Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and Ripple (XRP), based on their market capitalization from February 2018 to May 2025 and BRICS equity market. Additionally, this study focuses on dynamic evolution of the relationship between cryptocurrencies and BRICS equity markets by utilizing the time-varying parameter VAR (TVP-VAR) framework developed by Antonakakis and Gabauer (2020).

The contributions of this study are threefold. First, this study broadens the scope of existing research by examining return spillovers between the cryptocurrency and stock markets in the underexplored BRICS context. Second, we apply the TVP-VAR approach, which provides time-varying and event-driven dynamics. Third, we enhance the robustness of the results by delineating the period into three phases corresponding to the COVID-19 outbreak to highlight the dynamic evolution of spillover during periods of shocks.

## 2. Review of Literature

A plethora of studies have examined the relationship between cryptocurrencies and global stock markets (Alamaren *et al*., 2024; Niyitegeka& Zhou, 2023; Uzonwanne, 2021). In the context of developed economies, Uzonwanne (2021) examined return and volatility spillovers, elucidating unidirectional transmission from the UK and German equity markets to the Bitcoin market whereas bidirectional spillovers in the Japanese and US stock markets. Ali *et al*. (2024), by employing TVP-VAR, found green cryptocurrencies to be the receivers of volatility from the G7 stock markets, with further intensification during the COVID-19 pandemic. Additionally, Ahmed *et al*. (2023) through application of general-to-specific VAR (GETS-VAR) uncovered evidence of bidirectional spillovers between the S&P500 and cryptocurrencies, with equity market exerting a stronger influence on cryptocurrencies. Complementing this evidence, Aydoğan *et al*. (2022) reported bidirectional spillovers between cryptocurrencies and G7 equity markets. Meanwhile, Akyildirim *et al*. (2025) demonstrated unidirectional volatility transmission from cryptocurrency market to U.S. stock market using a TVP-VAR model.

Previous literature on emerging markets also provides evidence of cross-market linkages between the crypto-equity nexus. For instance, by employing the Generalized Method of Moments (GMM), Eldomiaty and Mohab (2024) reported a negative relationship between cryptocurrency and the Egyptian stock market. Empirical evidence from Asian equity markets revealed prominently unidirectional spillover from stock markets to cryptocurrencies. Chandra (2024) and Ustaoğlu (2022) reported equity to crypto spillover in context of the Indonesian and Turkish stock markets, respectively. Similar evidence was provided by Hussain *et al*. (2024) in case of Pakistani stock market. In contrast, Zhang *et al*. (2025) identified Thailand equity markets as transmitters of volatility spillovers. However, cryptocurrencies acted as transmitters in the context of return spillovers. Pertaining to BRICS equity market, Sindhu *et al*. (2025) concluded that cryptocurrencies were transmitters of return spillovers, while stock markets remained recipients.

The outbreak of COVID-19 pandemic disrupted global financial markets, resulting in increased uncertainty and intensification of cross-market connectedness (Akyildirim *et al*., 2025). Consistent with this, Iyer (2022) documented a surge in spillover during COVID-19, with volatility spillovers spiking by 12–16%, while the returns concurrently increased by 8–10%, with cryptocurrencies acting as transmitters. Sindhu *et al*. (2025) showed a surge in crypto-equity nexus during the pre-COVID-19 phase, with spillovers flowing from cryptocurrencies to equity markets. On the other hand, Balcilar *et al*. (2022) found an increase in volatility spillovers between cryptocurrencies and 27 emerging equity markets after the pandemic.

A different strand of literature has evidenced moderate or weak spillovers between cryptocurrency and equity markets. Trabelsi (2018) evidenced no significant spillover effects between cryptocurrency and traditional equity markets by adopting a spillover index approach. Recent evidence by Joseph *et al*. (2024) elucidated weak unidirectional spillover from cryptocurrency to African equities (Nigeria, South Africa, Egypt, Morocco, and Kenya) using the dynamic conditional correlation GARCH approach. A similar result was provided by Harb *et al*. (2024) while analyzing linkages in respect of U.S. equity market.

## 3. Data and Methodology

### *3.1 Data Description*

Our dataset consists of daily adjusted closing prices of the BRICS equity markets- IBOI (Brazil), MOEX (Russia), NIFTY 50 (India), SSE (China), and FTSE/JSE (South Africa) and the four largest cryptocurrencies- BTC, ETH, XRP, and BNB. These cryptocurrencies represent approximately 80% of the crypto market capitalization as of May 5, 2026 (CoinMarketCap, 2026). The data span from February 26, 2018 to May 16, 2025. This period was selected to ensure the uniform availability of data across all selected markets. To enhance the robustness of our results, we perform regime-specific analysis by segmenting the dataset into three sub-periods: pre-COVID-19 (February 26, 2018, to January 23, 2020), COVID-19 (February 3, 2020, to June 1, 2020), and post-COVID-19 (June 2, 2020, to May 16, 2025) (Bharti *et al*., 2025). The cryptocurrency and BRICS stock market data were sourced from www.CoinMarketCap.com and www.investing.com, respectively. The cryptocurrency data were aligned with the trading days of the equity markets, after which the final dataset resulted in 1664 observations. The daily return series was calculated using the log difference of consecutive prices to convert the data into stationarity.

### *3.2 Methodology*

We applied the TVP-VAR model to examine the return spillover between cryptocurrency and equity markets (Antonakakis *et al.*, 2020). The TVP-VAR is an acknowledged model from the VAR family that captures structural changes (Korkusuz, 2025)this study investigates the realized volatility spillover dynamics across major cryptocurrencies over an extended period of time. Using a Time-Varying Parameter Vector Autoregression (TVP-VAR. However, unlike standard VAR models, the TVP-VAR allows the coefficients and shock variances to change with respect to real-time data using the Kalman filter, capturing the non-linear and time-varying nature of financial linkages without restricting the rolling-window size (Sindhu *et al.*, 2025)"title-short":"Dynamic connectedness between Bitcoin and equity market information across BRICS countries","volume":"16","author":[{"family":"Dahir","given":"Ahmed Mohamed"},{"family":"Mahat","given":"Fauziah"},{"family":"Amin Noordin","given":"Bany-Ariffin"},{"family":"Hisyam Ab Razak","given":"Nazrul"}],"issued":{"date-parts":[["2020"]]}}}],"schema":"https://github.com/citation-style-language/schema/raw/master/csl-citation.json"} . The Kalman filter accounts for outliers and structural breaks, strengthening the estimation process for more accurate and reliable inferences.

The major strength of this method lies in its ability to manage multivariate systems, as compared to the traditional models that can only manage bivariate contexts. This aspect enhances the ability of TVP-VAR to identify complex relationships, which are essential for analyzing systemic spillovers between cryptocurrencies and equity markets. Additionally, it provides a thorough evaluation of the interconnectedness between variables by showing net and directional linkages. The basic TVP-VAR model is presented as:

$$Y_t = \varphi_t Y_{t-1} + \varepsilon_t, \varepsilon_t \sim \mathrm{N}(0, \alpha_t) \quad (1)$$

$$\mathrm{vec}(\varphi_t) = \mathrm{vec}(\varphi_{t-1}) + v_t, v_t \sim \mathrm{N}(0, \beta_t) \quad (2)$$

where, $Y_t, Y_{t-1}$and $\varepsilon_t$ denote $n \times 1$ vectors. The parameters $\varphi_t$and $\alpha_t$ represents $n \times n$ matrices whereas vec $(\varphi_t)$ and $v_t$ are $n^2 \times 1$ vectors. $\beta_t$ has dimensions of $n^2 \times n^2$. Further, both $\alpha_t$ and $\beta_t$ are time-varying variance-covariance matrices.

The generalized forecast error variance decomposition (GFEVD) method is used to obtain directional spillovers from variable *(j)* to variable *(i)* (Koop *et al.*, 1996). This approach explains the amount of forecast error variance happened in one variable due to another. The equation for GFEVD is as follows:

$$\tilde{\theta} i,j(H) = \frac{\sum_{t=1}^{H-1} ((\Psi_k \Sigma_\epsilon e_j)_i)^2 / \sigma_{jj}}{\sum_{k=0}^{H-1} ((\Psi_k \Sigma_\epsilon \acute{\Psi}_k))_{ii})} \quad (3)$$

In the above expression, $(\Psi_k \sum_\epsilon e_j)_i$ refers the $i^{th}$ vector element of $\Psi_k \sum_\epsilon e_j$ whereas $(\Psi_k \sum_\epsilon \acute{\Psi}_k)_{ii}$ corresponds to $i^{th}$ diagonal component of matrix $\Psi_k \sum_\epsilon \acute{\Psi}_k$ and H represents forecast horizon.

The total connectedness index (TCI) presents average interconnectedness among the variables. It is calculated by adding the off-diagonal values divided by the total number of elements $(n)$. The equation is as follows:

$$TCI(H) = \frac{1}{n} \sum_{i=1}^{n} \sum_{i=1, i \neq 1}^{n} \theta_{i,j}(H) \quad (4)$$

$T_{i \to \bullet}(H)$represents the contribution of shocks from variable $i$ to the forecast error variance of variable $j$ at horizon H. Based on this, the "TO" connectedness measures, as presented in equation 5, capture the total spillover transmitted by variable to the rest of the variables. Conversely, the "FROM" connectedness, denoted by, $T_{\bullet \to i}(H)$ in equation 6 reflects the total spillover received by variable $i$ from all other variables.

$$T_{i \to \bullet}(h) = \sum_{j=1, j \neq i}^{n} \theta_{ji}(H) \quad (5)$$

$$T_{\bullet \to i}(h) = \sum_{j=1, j \neq i}^{n} \theta_{ij}(H) \quad (6)$$

The "NET" connectedness is obtained by the difference in "TO" and "FROM" connectedness, denoted by $T_{i,t}$in equation 7. A positive value implies that the variable is a transmitter of shocks, while a negative value implies that the variable is a net receiver of shocks. It is calculated as follows:

$$T_{i,t} = T_{i\rightarrow\bullet}(H) - T_{\bullet\rightarrow i}(H) \qquad (7)$$

# 4. Results

## *4.1 Preliminary Analysis*

Table 1 presents the descriptive statistics of the returns of cryptocurrencies and BRICS equity markets for the full sample period. Among equity markets, India exhibits the highest daily average return (0.052%) with the lowest standard deviation (1.162%). In case of cryptocurrencies, BNB marks the largest mean returns (0.252%) while XRP emerges as the most volatile market (6.717%). Cryptocurrencies generate higher average returns than equity markets, but with considerably greater standard deviations. The return series exhibits negative skewness with a kurtosis value indicating a fat-tailed distribution. The ADF test confirms the stationarity of the series.

**Table 1: Descriptive Analysis**

| Variable | Brazil | Russia | India | China | South Africa | BTC | ETH | XRP | BNB |
|---|---|---|---|---|---|---|---|---|---|
| **Mean (%)** | -0.005 | 0.011 | 0.052 | 0.001 | 0.027 | 0.139 | 0.065 | 0.055 | 0.252 |
| **Standard Deviation** | 2.309 | 1.808 | 1.162 | 1.360 | 1.224 | 4.356 | 5.738 | 6.717 | 5.889 |
| **Minimum (%)** | -17.876 | -40.467 | -13.904 | -19.048 | -10.227 | -49.728 | -58.964 | -54.101 | -58.116 |
| **Maximum (%)** | 15.084 | 18.262 | 8.400 | 20.320 | 9.048 | 20.724 | 32.681 | 62.269 | 53.057 |
| **Skewness** | -0.628 | -6.359 | -1.405 | 0.429 | -0.439 | -0.877 | -0.688 | 1.212 | 0.029 |
| **Kurtosis** | 10.561 | 163.484 | 23.412 | 61.492 | 12.120 | 16.000 | 13.023 | 21.632 | 18.533 |
| **Jarque-Bera** | 4073.497*** | 1796902.0*** | 29435.98*** | 237260.70*** | 5820.159*** | 11930.340*** | 7096.530*** | 24475.930*** | 16727.720*** |
| **ADF** | -44.772*** | -44.119*** | -16.905*** | -45.805*** | -27.513*** | -41.717*** | -27.235*** | -39.936*** | -40.627*** |

***Note: *implies stationarity at the 10% significance level, ** implies stationarity at the 5% significance level, and *** implies stationarity at the 1% significance level.***
*Source*: Author's Own

## *4.2 Return Spillover Analysis for Full Period*

Table 2 demonstrates the return spillovers between cryptocurrencies and BRICS equity markets for full-sample analysis (2018-2025). The TCI of 43.74% signifies a moderate level of interconnectedness between the cryptocurrency and equity markets. The findings demonstrate cryptocurrencies as transmitters and equity markets as recipients. Specifically, ETH emerges as the prominent transmitter with a net connectedness of +13.85%. This was in quick succession, followed by BTC (+7.77%) and BNB (+0.80%). XRP is the sole net receiver (-1.33%) of return spillovers among cryptocurrencies. Among equity markets, India is the prominent receiver (-8.36%) of spillovers, followed by China (-6.56%). South African equity market is the only net transmitter (+0.89%).

The diagonal elements present the forecast error variance for each asset occurring due to idiosyncratic factors. Among cryptocurrencies, XRP (+44.67%) exhibits the highest level of idiosyncratic shock while

ETH shows the least idiosyncratic component. Within the BRICS markets, China (+79.51%) reports highest diagonal values, whereas South Africa (+59.62%) accounts for least values. Notably, equities are more susceptible to idiosyncratic risk, as demonstrated by the huge difference between the highest and lowest diagonal values.

**Table 2: Spillover Between Cryptocurrency and BRICS Equity Markets for Full Sample Period**

| Variable | Brazil | Russia | India | China | South Africa | BTC | ETH | XRP | BNB | FROM |
|---|---|---|---|---|---|---|---|---|---|---|
| **Brazil** | 71.24 | 4.47 | 3.92 | 1.47 | 8.45 | 2.70 | 2.58 | 2.42 | 2.76 | 28.76 |
| **Russia** | 4.59 | 72.40 | 4.69 | 1.43 | 7.71 | 2.46 | 2.63 | 1.95 | 2.14 | 27.60 |
| **India** | 5.53 | 4.77 | 67.75 | 3.16 | 10.14 | 1.73 | 2.92 | 2.02 | 1.98 | 32.25 |
| **China** | 2.58 | 1.85 | 3.59 | 79.51 | 7.38 | 0.94 | 1.46 | 1.22 | 1.47 | 20.49 |
| **South Africa** | 7.65 | 6.86 | 7.85 | 5.44 | 59.62 | 3.10 | 3.56 | 2.60 | 3.32 | 40.38 |
| **BTC** | 1.51 | 1.27 | 0.67 | 0.45 | 1.90 | 37.39 | 25.60 | 14.51 | 16.70 | 62.61 |
| **ETH** | 1.54 | 1.33 | 1.40 | 0.59 | 1.99 | 24.27 | 35.41 | 16.41 | 17.06 | 64.59 |
| **XRP** | 1.53 | 1.10 | 0.83 | 0.55 | 1.69 | 16.64 | 19.75 | 44.67 | 13.25 | 55.33 |
| **BNB** | 1.69 | 1.00 | 0.93 | 0.83 | 2.02 | 18.54 | 19.97 | 12.89 | 42.13 | 57.87 |
| **TO** | 26.62 | 22.65 | 23.89 | 13.93 | 41.27 | 70.39 | 78.47 | 54.01 | 58.68 | 389.90 |
| **Including Own** | 97.86 | 95.05 | 91.64 | 93.44 | 100.89 | 107.77 | 113.88 | 98.67 | 100.80 | TCI |
| **NET** | -2.14 | -4.95 | **-8.36** | -6.56 | **0.89** | **7.77** | **13.88** | **-1.33** | 0.80 | **43.32** |

*Note: *All values are expressed as percentages. A lag length of order one was selected using the Bayesian Information Criterion (BIC), and a forecast error variance of 10 days was adopted. Bold values indicate prominent transmitters (receivers).*

*Source*: Author's Own

Figure 1 presents the time-varying net directional connectedness, illustrating the evolution of net position of these markets. The area above zero mark represents the market as transmitter while below it denotes the reception state. Among cryptocurrencies, the dynamic plots demonstrate the dominant transmission role of ETH and BTC, complementing the results presented in Table 2. These cryptocurrencies consistently functioned as transmitters throughout the sample period, representing that the transmission is structural rather than event driven. On the other hand, BNB fluctuates between transmitting and receiving role, whereas XRP shifts to net receiving position after a serving as strong transmitter during the year 2018. For BRICS equity markets, the figure further exhibits its vulnerability to external shocks, validating their position as receivers. Indian and Chinese equity market remain embedded in the negative zone, confirming their role as prominent receivers. Notably, Chinese equity market reported a pronounced negative dive in 2020. Brazil and Russia largely centered around the zero line with remarkable spike occurring during periods of uncertainty. South Africa demonstrates a unique spillover profile, with a net transmitter role even during the COVID-19 pandemic, with only short-lived periods of being vulnerable to spillovers, distinguishing it from the remaining BRICS equity markets.

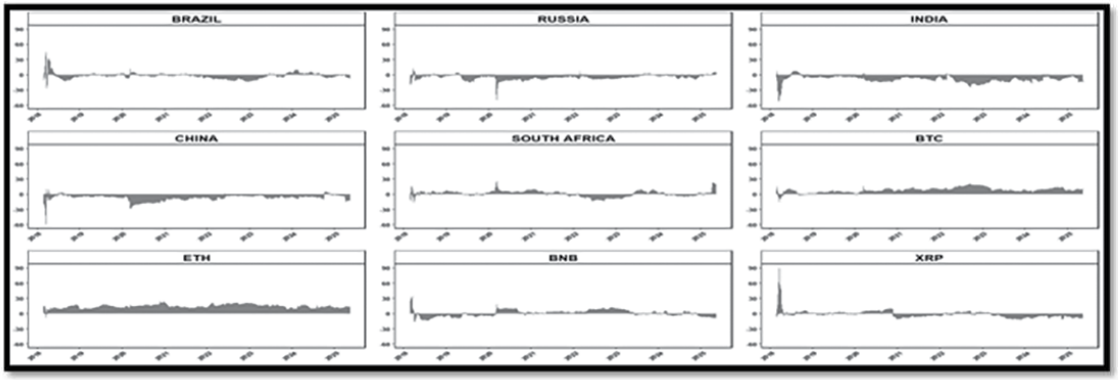


**Figure 1:** Net Return Spillover across Markets

*Source: Author's Own*

Figure 2 graphically captures the evolution of total connectedness between cryptocurrencies and equity markets, revealing regime-dependent integration. The level of connectedness remained between 30-50% during tranquil periods, with notable spikes in 2018 and 2020. The early 2018 witnessed US-China trade conflicts and a ban on cryptocurrency advertisements by various social media platforms, resulting in widespread spillover. The second spike in TCI occurred during the initial phase of the pandemic in 2020. The decrease in the consumer confidence index, combined with shutdowns around the world, caused investor panic, and the crash in the stock market led to the amplification of the return spillovers, and connectedness grew up to 70%. This finding is supported by contagion theory, which suggests that during crises, market interconnectedness rises beyond what can be explained by economic fundamentals. After the pandemic, total connectedness remained elevated at approximately 45%-50%, reflecting a secondary phase of contagion triggered by the combined effects of the Russia–Ukraine conflict and FTX collapse. Thereafter, the TCI declined steadily, suggesting a gradual easing of return spillovers.

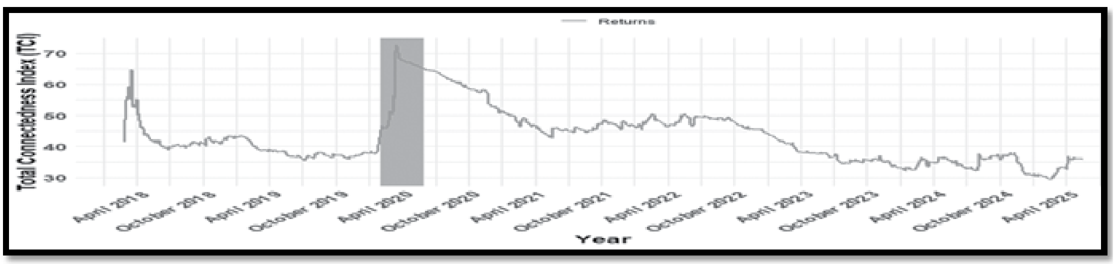


**Figure 2:** TCI over the years

*Source: Author's Own*

### *4.3 Spillover Analysis for Segmented Periods*

Next, we test the conjecture that the spillovers across equity and cryptocurrency markets are influenced by the COVID-19 pandemic. Table 3 depicts the regime-specific connectedness analysis for three phases: pre-COVID-19 (Panel A), during COVID-19 (Panel B), and post-COVID-19 (Panel C). The results show a pivotal intensification of cross-market linkages during the COVID-19 pandemic, with a TCI of 72.72%. Cryptocurrencies emerge as transmitters of spillovers across all sub-periods. Specifically, ETH consistently acts as a prominent transmitter, reinforcing its importance in crypto-equity spillovers. Concerning equity markets, Russia (-7.10%), China (-39.09%), and India (-9.68%) emerge as prominent recipients of spillovers in the pre-COVID-19, during COVID-19, and post-COVID-19 phases, respectively. Interestingly, the South African equity market functioned as a net transmitter during the pre-COVID-19 (+0.09%) and COVID-19 (8.01%) periods but shifted to a net receiver in the post-COVID-19 period (-2.84%).

**Table 3: Return Spillover between cryptocurrency and BRICS equity market during sub-periods**

| **Panel A: Pre-COVID-19** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Brazil** | **Russia** | **India** | **China** | **South Africa** | **BTC** | **ETH** | **XRP** | **BNB** | **FROM** |
| **Brazil** | 82.23 | 6.54 | 2.03 | 1.12 | 2.87 | 1.84 | 1.16 | 1.40 | 0.80 | 17.77 |
| **Russia** | 6.81 | 69.39 | 2.95 | 2.92 | 9.39 | 1.68 | 1.64 | 2.67 | 2.55 | 30.61 |
| **India** | 1.66 | 2.65 | 78.70 | 5.43 | 6.40 | 1.27 | 1.09 | 1.80 | 0.99 | 21.30 |
| **China** | 2.45 | 2.74 | 4.47 | 71.74 | 13.08 | 0.93 | 0.99 | 1.66 | 1.94 | 28.26 |
| **South Africa** | 2.74 | 8.64 | 5.95 | 12.08 | 65.55 | 1.07 | 0.86 | 1.54 | 1.57 | 34.45 |
| **BTC** | 0.49 | 0.72 | 0.90 | 0.97 | 0.72 | 39.68 | 25.01 | 18.70 | 12.80 | 60.32 |
| **ETH** | 0.55 | 0.51 | 0.52 | 0.95 | 0.64 | 23.04 | 36.65 | 23.09 | 14.06 | 63.35 |
| **XRP** | 0.60 | 1.04 | 1.01 | 1.18 | 0.85 | 19.03 | 25.35 | 40.67 | 10.26 | 59.33 |
| **BNB** | 0.55 | 0.66 | 1.35 | 1.65 | 0.60 | 15.37 | 18.63 | 12.93 | 48.27 | 51.73 |
| **TO** | 15.86 | 23.50 | 19.19 | 26.31 | 34.55 | 64.25 | 74.71 | 63.79 | 44.96 | 367.12 |
| **Including Own** | 98.09 | 92.90 | 97.89 | 98.05 | 100.09 | 103.92 | 111.36 | 104.46 | 93.23 | TCI |
| **NET** | -1.91 | **-7.10** | -2.11 | -1.95 | **0.09** | 3.92 | **11.36** | 4.46 | **-6.77** | **40.79** |
| **Panel B: During COVID-19** | | | | | | | | | | |
| **Variable** | **Brazil** | **Russia** | **India** | **China** | **South Africa** | **BTC** | **ETH** | **XRP** | **BNB** | **FROM** |
| **Brazil** | 27.48 | 7.88 | 12.89 | 3.92 | 15.07 | 9.41 | 9.06 | 5.85 | 8.45 | 72.52 |
| **Russia** | 12.09 | 36.28 | 7.43 | 2.10 | 12.08 | 9.21 | 8.56 | 5.15 | 7.10 | 63.72 |
| **India** | 12.23 | 7.03 | 34.40 | 9.62 | 14.09 | 4.09 | 5.91 | 6.53 | 6.09 | 65.60 |
| **China** | 6.71 | 8.57 | 10.03 | 28.73 | 9.44 | 6.31 | 8.41 | 12.70 | 9.09 | 71.27 |
| **South Africa** | 14.07 | 8.82 | 14.99 | 6.02 | 29.45 | 6.35 | 7.09 | 5.84 | 7.36 | 70.55 |
| **BTC** | 6.24 | 6.66 | 3.42 | 1.03 | 6.59 | 23.94 | 20.35 | 13.80 | 17.98 | 76.06 |
| **ETH** | 6.42 | 7.32 | 4.17 | 2.79 | 7.23 | 18.77 | 20.47 | 15.12 | 17.72 | 79.53 |
| **XRP** | 5.47 | 6.71 | 4.38 | 3.60 | 6.57 | 15.10 | 17.74 | 23.37 | 17.07 | 76.63 |
| **BNB** | 5.91 | 5.47 | 4.62 | 3.08 | 7.49 | 17.54 | 19.07 | 15.46 | 21.36 | 78.64 |
| **TO** | 69.14 | 58.46 | 61.92 | 32.17 | 78.56 | 86.78 | 96.18 | 80.44 | 90.86 | 654.52 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Including Own** | 96.63 | 94.75 | 96.32 | 60.91 | 108.01 | 110.72 | 116.65 | 103.80 | 112.22 | TCI |
| **NET** | -3.37 | -5.25 | -3.68 | **-39.09** | 8.01 | 10.72 | **16.65** | 3.80 | 12.22 | **72.72** |
| **Panel C: Post-COVID-19** | | | | | | | | | | |
| **Variable** | **Brazil** | **Russia** | **India** | **China** | **South Africa** | **BTC** | **ETH** | **XRP** | **BNB** | **FROM** |
| **Brazil** | 72.14 | 2.85 | 3.53 | 1.10 | 9.28 | 3.09 | 2.59 | 2.63 | 2.79 | 27.86 |
| **Russia** | 2.08 | 79.74 | 5.57 | 0.98 | 5.40 | 1.79 | 2.12 | 1.20 | 1.11 | 20.26 |
| **India** | 4.91 | 5.03 | 68.36 | 1.95 | 8.74 | 2.37 | 4.06 | 2.51 | 2.08 | 31.64 |
| **China** | 1.59 | 1.26 | 2.26 | 84.51 | 4.19 | 1.09 | 2.30 | 1.35 | 1.45 | 15.49 |
| **South Africa** | 8.13 | 4.94 | 6.98 | 3.15 | 62.12 | 3.64 | 4.33 | 2.82 | 3.89 | 37.88 |
| **BTC** | 1.56 | 0.81 | 0.68 | 0.45 | 1.89 | 38.77 | 25.89 | 12.65 | 17.31 | 61.23 |
| **ETH** | 1.30 | 1.05 | 1.58 | 0.63 | 1.91 | 25.03 | 37.53 | 13.73 | 17.27 | 62.47 |
| **XRP** | 1.39 | 0.64 | 0.74 | 0.58 | 1.56 | 15.37 | 17.31 | 49.11 | 13.28 | 50.89 |
| **BNB** | 1.63 | 0.58 | 0.63 | 0.58 | 2.07 | 19.20 | 19.72 | 12.18 | 43.41 | 56.59 |
| **TO** | 22.58 | 17.18 | 21.96 | 9.42 | 35.04 | 71.58 | 78.31 | 49.07 | 59.18 | 364.32 |
| **Including Own** | 94.72 | 96.92 | 90.32 | 93.93 | 97.16 | 110.34 | 115.83 | 98.19 | 102.58 | TCI |
| **NET** | -5.28 | -3.08 | **-9.68** | -6.07 | -2.84 | 10.34 | **15.83** | -1.81 | 2.58 | **40.48** |

*Note: *All values are expressed as percentages. A lag length of order one was selected using the BIC, and a forecast error variance of 10 days was adopted. Bold values indicate prominent transmitters (receivers). The table presents the analysis for periods: pre-COVID-19 (February 26, 2018, to January 23, 2020), COVID-19 (February 3, 2020, to June 1, 2020), and post-COVID-19 periods (June 2, 2020, to May 16, 2025).*
*Source*: Author's Own

## 5. Discussion

The findings of this study show that cryptocurrencies are prominent transmitters of spillovers, whereas BRICS equity markets are net recipients. ETH plays a more influential role in spillovers than BTC because of its pivotal role in decentralized finance and smart contracts (Korkusuz, 2025). The crypto to equity transmission can be attributed to disparities in market structure and informational efficiency. Continuous cryptocurrency trading enables faster incorporation of macroeconomic shocks, which are subsequently transmitted to equity markets (Alana *et al*., 2020). This transmission can occur through several channels. First, herding behavior among investors can facilitate transmission even in the absence of a direct fundamental linkage (Bharti and Kumar, 2022). Second, transmission mechanisms can be reinforced through portfolio rebalancing, as highly volatile cryptocurrency market prompts investors to reassess ass*et al*location in order to maintain the stability and security of capital. Further, the sharp swings in the cryptocurrency market often trigger speculative trading and arbitrage (Aydoğan *et al*., 2022). When leveraged, such volatility may cause a margin call or forced liquidation, thereby transmitting price pressures into the stock market. Finally, institutional linkages, especially technology sectors stocks, including those specializing in blockchain and fintech serve as potential transmission channels, connecting cryptocurrencies and stock markets (Akyildirim *et al*., 2025). The results are in line with the findings of Joseph *et al*. (2024), who demonstrated moderate spillovers.

The COVID-19 crisis marked a phase of contagion, with the TCI escalating from 40.79% to 72.72%. During this period, accelerated digitalization due to lockdowns across the globe provoked the massive use of cryptocurrencies and fintech apps by retail and institutional investors, resulting in stronger crypto-equity linkages (Niyitegeka and Zhou, 2023; Sindhu *et al*., 2025). According to Coingecko, cryptocurrencies emerged as a prominent topic globally, with the total trading volume rising from approximately USD 14 billion in February, 2019 to USD 115 billion in March, 2020. Furthermore, spillover may have been amplified by statements from high-profile figures, such as Tesla's Elon Musk, regarding cryptocurrencies. Consequently, the amplification of crypto-equity spillovers reduces the diversification and hedging effectiveness of cryptocurrencies during turbulent market conditions. These results are supported by Alamaren *et al*. (2024), Akyildirim *et al* (2025), Iyer (2022) and Niyitegeka and Zhou (2023).

## 6. Conclusion, Implications, and Limitations

This study examines the return spillovers between select cryptocurrencies and BRICS equity markets from 2018 to 2025 using the TVP-VAR model. The results present cryptocurrencies, mainly ETH, as the main transmitter and BRICS equity markets as receiver of spillovers. Among the BRICS equity markets, India emerges as the most vulnerable to crypto shocks. Time-varying analysis demonstrates increased integration between the equity and cryptocurrency markets, particularly in 2018 and during the COVID-19 period. This evidence is further supported by sub-period analysis, which reports the intensification of spillovers with total connectedness reaching 72.72% during the pandemic.

### *Implications*

Our findings have important implications for emerging markets, as evidence of increased integration with highly volatile cryptocurrencies poses significant risks to market stability. For regulators and policymakers, a consistently strong spillover from cryptocurrency to equity markets stresses the need for effective risk monitoring and surveillance mechanisms, disclosure requirements related to crypto exposure, stringent regulations, and improved infrastructure to minimize the impact of cryptocurrency-driven uncertainties. Investors should exercise utmost caution when using cryptocurrencies for diversification, as the increased correlation during crises may result in contagions. Further, the discovery of cryptocurrencies as systemic shock transmitters stresses the necessity of adopting a portfolio diversification strategy that embraces changing market conditions instead of a static "buy-and-hold" strategy.

### *Limitations and Future Recommendations*

However, this study has limitations that provide directions for future research. *First*, examination of volatility spillover between cryptocurrencies and BRICS equity can be undertaken to provide deeper insights into the spillover mechanism. *Second*, the analysis is limited to four major cryptocurrencies. Future studies can incorporate modern altcoins that can have different impacts on spillover dynamics. Moreover, cryptocurrencies may be classified into large, medium, and small sizes based on their market capitalization to capture asymmetry in spillovers. *Third,* subsequent studies can extend their analysis to other emerging blocks to examine the consistency of crypto-equity linkages. Further, a comparative analysis of emerging and developed economies can help determine whether economic maturity influences interconnectedness. *Finally*, future studies may analyze the influence of major macroeconomic factors, such as interest rates, economic uncertainty index, or financial stress index, on the intensity of connectedness.

## Statements and declarations

**Conflicting interests:** The authors declare no potential conflicts of interest with respect to the research, authorship, or publication of this study.

## References


- Ahmed, M. Y., Sarkodie, S. A. & Leirvik, T. (2023) 'Mutual coupling between stock market and cryptocurrencies', *Heliyon*, 9(5). Available at: https://www.cell.com/heliyon/fulltext/S2405-8440(23)03386-8.
- Akyildirim, E., Corbet, S., Coskun, A. & Ercan, M. (2025) 'Connectedness of cryptocurrency-related stocks and the cryptocurrency market: Evidence from the United States', *The North American Journal of Economics and Finance*, 76, p. 102344. Available at: https://doi.org/10.1016/j.najef.2024.102344.
- Alamaren, A. S., Gokmenoglu, K. K. & Taspinar, N. (2024) 'Volatility spillovers among leading cryptocurrencies and US energy and technology companies', *Financial Innovation*, 10(1), p. 81. Available at: https://doi.org/10.1186/s40854-024-00626-2.
- Alana, G. L. A., Abakah, E. J. A. & Rojo, M. F. R. (2020) 'Cryptocurrencies and stock market indices: Are they related?', *Research in International Business and Finance*, 51, p. 101063.
- Ali, S., Naveed, M., Yousaf, I. & Khattak, M. S. (2024) 'From cryptos to consciousness: Dynamics of return and volatility spillover between green cryptocurrencies and G7 markets', *Finance Research Letters*, 60, p. 104899.
- Antonakakis, N., Chatziantoniou, I. & Gabauer, D. (2020) 'Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions', *Journal of Risk and Financial Management*, 13(4), p. 84.
- Aydoğan, B., Vardar, G. & Taçoğlu, C. (2022) 'Volatility spillovers among G7, E7 stock markets and cryptocurrencies', *Journal of Economic and Administrative Sciences*, 40(2), pp. 364-387. Available at: https://doi.org/10.1108/JEAS-09-2021-0190.
- Balcilar, M., Ozdemir, H. & Agan, B. (2022) 'Effects of COVID-19 on cryptocurrency and emerging market connectedness: Empirical evidence from quantile, frequency, and lasso networks', *Physica A: Statistical Mechanics and Its Applications*, 604, p. 127885.
- Bharti & Kumar, A. (2022) 'Exploring herding behaviour in Indian equity market during COVID-19 pandemic: Impact of volatility and government response', *Millennial Asia*, 13(3), pp. 513-531. Available at: https://doi.org/10.1177/0976399621102068.
- Bharti, Gupta, S. & Kumar, A. (2025) 'Quantile regression modelling of herd behaviour in the Indian equity market across sectors: Implications on financial market dynamics spanning the COVID-19 epoch', *Journal of Modelling in Management*, 20(6), pp. 1912-1936. Available at: https://doi.org/10.1108/JM2-10-2024-0347.
- Chandra, R. (2024) 'Intermarket influence between traditional stock markets and cryptocurrencies: A case study of JSX and BTC', *JMBI UNSRAT (JurnalIlmiahManajemenBisnis Dan Inovasi Universitas Sam Ratulangi)*, 11(2), Article 2. Available at: https://doi.org/10.35794/jmbi.v11i1.57609
- CoinMarketCap (2026) 'Cryptocurrency prices, charts and market capitalizations'. Available at:

https://coinmarketcap.com (Accessed: 5 May 2026)

- Diaconaşu, D. E., Mehdian, S. M., Stoica, O. (2023) 'The reaction of financial markets to Russia's invasion of Ukraine: Evidence from gold, oil, Bitcoin, and major stock markets', *Applied Economics Letters,* 30*,* pp. 2792-2796. Available at: https://doi.org/10.1080/13504851.2022.2107608.
- El Hajj, M., Farran, I. (2024) 'The Cryptocurrencies in emerging markets: Enhancing financial inclusion and economic empowerment', *Journal of Risk and Financial Management,* 17, p. 467. Available at: https://doi.org/10.3390/jrfm17100467.
- Eldomiaty, T., & Mohab, N. (2024) 'Cryptocurrency volatility and Egyptian stock market indexes: A note', *Modern Finance*, 2(1), pp. 121–130.
- Harb, E., Bassil, C., Kassamany, T., & Baz, R. (2024) 'Volatility Interdependence Between Cryptocurrencies, Equity, and Bond Markets', *Computational Economics*, 63(3), pp. 951–981. Available at: https://doi.org/10.1007/s10614-022-10318-7
- Hussain, I., Ali, N., Ahmad, H. B., & Ashraf, S. (2024) 'Volatility spillover effect between cryptocurrency and stock market using MGARCH BEKK model', *Natural and Applied Sciences International Journal (NASIJ)*, 5(2), pp. 32–55.
- Iyer, T. (2022) '*Cryptic Connections: Spillovers Between Crypto and Equity Markets',* International Monetary Fund.
- Joseph, T. E., Jahanger, A., Onwe, J. C., &Balsalobre-Lorente, D. (2024) 'The implication of cryptocurrency volatility on five largest African financial system stability', *Financial Innovation*, 10(1), p. 42. Available at: https://doi.org/10.1186/s40854-023-00580-5
- Koop, G., Pesaran, M. H., & Potter, S. M. (1996) 'Impulse response analysis in non-linear multivariate models', *Journal of Econometrics*, 74(1), pp. 119–147.
- Korkusuz, B. (2025) 'Volatility Transmission in Digital Assets: Ethereum's Rising Influence', *Journal of Risk and Financial Management*, 18(3), Article 3. Available at: https://doi.org/10.3390/jrfm18030111
- Niyitegeka, O., & Zhou, S. (2023) 'An investigation of financial contagion between cryptocurrency and equity markets: Evidence from developed and emerging markets', *Cogent Economics & Finance*, 11(1), p. 2203432. Available at: https://doi.org/10.1080/23322039.2023.2203432
- Sindhu, M. I., Wong, W.-K., & Maswadi, L. (2025) 'Unveiling Hidden Connectedness between Cryptocurrency and Stock Markets in BRICS: A TVP-VAR Perspective', *Kybernetes*. Available at: https://www.emerald.com/insight/content/doi/10.1108/K-10-2024
- Trabelsi, N. (2018) 'Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes?', *Journal of Risk and Financial Management*, 11(4), p. 66.
- Ustaoğlu, E. (2022) 'Return and Volatility Spillover between Cryptocurrency and Stock Markets: Evidence from Turkey', *MuhasebeveFinansman Dergisi*, 93, pp. 117–126. Available at: https://doi.org/10.25095/mufad.1024160
- Uzonwanne, G. (2021) 'Volatility and return spillovers between stock markets and cryptocurrencies', *The Quarterly Review of Economics and Finance*, 82, pp. 30–36.
- Zhang, Y., Lo, S., &Sutthiphisal, D. (2025) 'Inter-Market Mean and Volatility Spillover Dynamics Between Cryptocurrencies and an Emerging Stock Market: Evidence from Thailand and Sectoral Analysis', *Risks*, 13(4), Article 4. Available at: https://doi.org/10.3390/risks13040077

http://doi.org/10.56411/anusandhan.2026.v8i1.59

## Book Review

# Book Name: Impact of Blockchain in HRM

Reviewed by:

Divya Kataria

IT Professional, Faridabad, 121005

**ORCID: 0009-0000-3612-9103**

**Date of receiving the manuscript: May 20, 2026** **Date of publication: August 31, 2026**

The book "Impact of Block Chain in HRM" authored by Isha Kataria and co-authors is a contemporary academic contribution that explores the integration of blockchain technology with Human Resource Management (HRM). Organizations are progressively implementing cutting-edge technology in the age of digital transformation to enhance personnel management systems, efficiency, and transparency. This book effectively illustrates how blockchain technology may change HR procedures like hiring, payroll administration, employee verification, performance reviews, and data protection.

By offering conceptual knowledge and practical ramifications, the writers have made an effort to close the gap between technological innovation and HR functions. In the current business climate, where companies are shifting to automation and digital HR processes, the topic is quite pertinent. According to recent scholarly research, block chain improves HR operations' efficiency, security, transparency, and trust. The book's easy-to-read language is one of its main advantages. Even readers who are not technical can easily understand the explanations of block chain-related technological ideas. The book improves learning by skilfully fusing theoretical information with real-world situations.

The topic's relevancy is another crucial factor. Because block chain technology makes it possible for secure payroll systems, transparent hiring procedures, and tamper-proof employee records, it is becoming a transformative force in HRM. The book makes a substantial contribution to the growing body of knowledge on blockchain applications and digital HRM. For academics, researchers interested in technology-driven HR practices, management students, and HR professionals, it offers insightful information.

Overall, Impact of Block Chain in HRM is a perceptive and educational academic article that effectively illustrates the expanding position of blockchain technology in revolutionizing HRM procedures. The book is helpful for comprehending how businesses can use blockchain for HR operations that are transparent, effective, secure, and trustworthy.

**AUTHORS:** Isha Kataria et al. **PUBLISHER:** Alpha International Publication

## Registration Particulars

| | | | |
|---|---|---|---|
| 1. | Title of Publication | : | Anusandhan - NDIM's Journal of Business and Management Research |
| 2. | Language of publication | : | English |
| 3. | Periodicity of Publication | : | Bi-annual |
| 4. | Annual subscription fee | : | Rs. 1000/- per Annum |
| 5. | Publisher's Name | : | Dr. Bindu Kumar (Chairperson) for and on behalf of New Delhi Institute of Management |
| 6. | Nationality | : | Indian |
| 7. | Printed at | : | Viba Press Pvt. Ltd., C-66/3, Okhla Industrial Area, Okhla Phase II, New Delhi-110020 |
| 8. | Owner's Name | : | New Delhi Institute of Management |
| 9. | Particulars of the Society or Association which owns the Journal | : | A unit of Society for Employment & Career Counseling (Regd.) |

Published and Printed by Dr. Bindu Kumar, for and on behalf of New Delhi Institute of Management, 61, Tughlakabad Institutional Area, New Delhi -110062




Link for details of Editorial Policy

https://www.ndim.edu.in/anusandhan-guidelines

RNI DELENG/2029/83461

& Printed at : Vibha Press Pvt. Ltd., 981 004 9515