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# Adoption of AI in HR Practices: A Study of Talent Acquisition in North-East India

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**Abstract:** Artificial intelligence (AI) has revolutionised global talent-hiring processes but the impact of AI in regions that have unique socio-economic realities in North East India has remained understudied. The current study evaluates the contributions of competency, effectiveness, perceived ease of use and perceived usefulness to the adoption of AI by HR professionals in talent acquisition within the region. The questionnaire was structured, and 328 practitioners in various industries were given the questionnaire, and the results were analysed using factor analysis and multiple regressions. The results point to perceived ease of use and perceived usefulness as the main factors of AI adoption. Respondents prefer those tools that are user-friendly and bring instant benefits, especially when it comes to the simplification of the recruitment processes and candidate screening. On the contrary, competency and effectiveness do not have any significant impacts, and this could be due to the constraints in technical expertise and training. That is why the study indicates the importance of designing programs that are accessible and locally relevant AI applications in the context of uneven diffusion of technology. The research adds to the international discussions about the automation of HR and underlines the necessity of localised AI solutions. The findings provide practical recommendations to the HR practitioners who are willing to incorporate AI into talent acquisition practices and place them in the context of the overall scope of AI contribution to the recruitment process.

## 1. Introduction

The fast development of Artificial Intelligence (AI) is transforming talent acquisition practice worldwide, and North East India is not an exception. This study investigates the ways in which AI is having a transformative impact on talent acquisition in the area, and in particular how it is impacting competency, effectiveness, ease of use, and perceived usefulness, so as to gain insights into how these technological advancements are changing approaches to recruitment and organisational performance in this distinctive environment.

Artificial intelligence (AI) in talent acquisition is changing the way recruitment is carried out because it automates the process of screening resumes, finding candidates, and the initial interview, thus making the process more efficient, competent, and better decision-making (Chien, 2020; Binns, 2018). The candidate experience is being enhanced with recruitment systems driven by AI, which have the ability to offer personalised communication and real-time updates, which is in line with contemporary expectations of a smooth process (Nair & George, 2021). Nevertheless, AI in recruitment has a number of concerns, e.g., algorithmic bias, i.e., the fact that AI systems trained on past data may unintentionally reproduce the existing bias based on gender, ethnicity, or socio-economic background (Binns, 2018). Also, the issue of data privacy and the combination of AI and conventional HR activities pose serious risks, especially in such a region as North East India, where the legislative framework and the infrastructure to offer advanced technologies might be underdeveloped (Chien, 2020; Soni & Kumar, 2019). Moreover, the applicability of AI in the local setting, where demographic and cultural variations should be taken into account, is still an issue, and the adoption of AI systems by both HR professionals and candidates is always received with hesitation because of the perceived absence of human interaction in decision-making (Soni & Kumar, 2019; Nair & George, 2021). Finally, implementing AI may be too expensive to most organisations within North East India, which further restricts the use of AI in the region (Chien, 2020). Therefore, although AI can transform the process of talent acquisition, such tendencies, problems, and challenges must be overcome in order to integrate AI into the practice of regional talent acquisition.

The study of the influence of AI on talent acquisition in North East India is influenced by some of the established theories that investigate the issues of technology adoption, effectiveness, and user experiences. The Technology Acceptance Model (TAM), proposed by Davis (1989), has been a cornerstone in understanding how perceived ease of use and perceived usefulness influence individuals' willingness to adopt new technologies. Likewise, Unified Theory of Acceptance and Use of Technology (UTAUT) created by Venkatesh et al. (2003) further elaborated on TAM by including other constructs of performance expectancy and social influence, which also help to understand the influence of AI on talent acquisition practices. Also, the Resource-Based View (RBV) theory states that organisations can achieve competitive advantage by integrating valuable, rare, and inimitable resources such as AI technologies (Barney, 1991). Additionally, the theory of Diffusion of Innovations (DOI) by Rogers (2003) can be used to understand the diffusion of innovations, including AI within social systems and the determinants that determine the adoption rates in various geographical locations like North East India. These theoretical frameworks collectively inform the study's exploration of AI's role in enhancing competency, effectiveness, ease of use, and usefulness in talent acquisition within this specific region.

Artificial intelligence (AI) has been a quickly adopted technology in talent acquisition and has transformed the recruitment system in the world, but its influence on talent acquisition in North East India has not been explored. The purpose of the research is to assess the impact of AI on the competency, effectiveness, ease of use, and usefulness in the case of recruitment in this peculiar regional environment. Although AI could improve the efficiency and decision-making process of hiring, the limitations of the infrastructure, regional differences in the use of technology, and the issue of data privacy and bias might interfere with its efficiency. Relevance of the study can be attributed to the fact that the study is conducted in North East India which has quite different demographic, cultural and economic attributes and where AI has not been extensively used in HR practices. Through the investigation on the effect of AI on recruitment in this region, the research will provide meaningful information to organisations, policymakers, and HR professionals to optimally implement AI in this region taking into consideration the challenges in this region. The study is critical in explaining the potential of AI to be applied in talent acquisition procedures in areas that have different and changing requirements.

Artificial Intelligence (AI) can revolutionise HRM (Human Resource Management), especially regarding talent acquisition. Organisations aiming to enhance their success rate must explore how artificial intelligence can streamline repetitive tasks, deliver precise measurements, and facilitate decision-making processes. Although the global excitement around AI-driven recruitment has been immense, almost no conversations are taking place about the unique opportunities and challenges facing different regions of the world like North East India. This gap provides an opportunity for research on how AI technology can improve the accuracy, efficiency, price competitiveness and convenience of talent attraction in a uniquely set organisational ecology.

This research contributes to the understanding of how artificial intelligence deployment impacts recruitment processes in the human resources sectors of North East India, addressing a gap in existing literature and empirical evidence on this topic. While most studies have elaborated on the advantages of AI in global recruitment, more is needed to know about how they operate in regions with unique socio-economic and cultural dynamics like North East India. Studies like Pills & Sivathanu (2020) and Vedapradha et al. (2023) have elucidated the previous work. Studies for the future have already shown the positive outlook from applications of AI in recruitment and management roles; however, how such changes are perceived among HR professionals from a region like North East India is yet to be uncovered.

This study stands out by analysing four key aspects in relation to AI-driven recruitment: Competency, Effectiveness (encompassing both task and outcome), Perceived ease of use, and usefulness. It uniquely explores these attributes within the context of artificial intelligence-based hiring processes.

These findings are specific to the local context of North East India and can be extrapolated in other similar settings. This research not only addresses a crucial gap in the literature but also provides recommendations for human resources practitioners in an alternative geographical area.

With northeast India developing its own economic and technological landscape, AI can help North East India attract talent and be competitive. As such, the current study aims to theoretically broaden academic discussions on AI in HRM and practically by providing valuable insights for HR practitioners.

With the context and importance of the given study determined, it is essential to analyse the available body of literature to comprehend the current situation with regards to AI in talent acquisition, especially in such a region as North East India. The literature review will analyse the past research on the use of AI in recruitment with emphasis on competency, effectiveness, ease of use and usefulness. The challenges and barriers to the adoption of AI will also be covered in this part, and so will the implications of the same in the regional context. The literature review will also synthesise the existing literature to identify the gaps and establish the theoretical framework of the current research and also provide a basis to comprehend how AI could be used to define the future of talent acquisition in North East India.

## 2. Review of Literature

The use of Artificial Intelligence (AI) in executing the talent acquisition process has drastically changed how enterprises look for and employ talent. As expected, recruitment has also been renovated with machines taking on the role of human recruiter and performing their job faster, efficiently and cost-effectively thanks to technologies such as AI. AI can automatically handle routine activities like resume filtering, scheduling interviews, and even conducting initial candidate evaluations, enabling HR specialists to take care of additional strategic facets of talent acquisition (Yadav et al., 2023).

It reduced time-to-hire, improved the accuracy of candidate matching and left recruiters with better talent. This, for example, was the case with Unilever: Using AI in their recruitment processes, automated interview analysis, and gamified assessments saves time and money to hire while providing a better candidate experience (Hu, 2023). In addition, AI-based tools can help organisations develop novel and more inclusive workforces by reducing the biases often associated with human recruiters (Liu & Murphy, 2022).

Studies have also shown that using AI allows organisations to handle many job applications more efficiently and provide more individualised and timely service for the candidate throughout the hiring process. This helps strengthen their employer brand, which is key to attracting top talents (Baratelli & Colleoni, 2022). Moreover, AI aids HR teams with the sourcing of candidates in a more accurate and faster manner by using machine algorithms to detect which candidates better match each role through data-based insights (Pillai & Sivathanu, 2020).

Competency is an important criterion for adopting AI. In other words, it is about the competence of your AI system and all HR professionals working towards optimising their talent acquisition process. Chen et al. (2021) apply AI tools to predict job candidates' competency levels, which helps make more optimised recruitment decisions by analysing factors like knowledge, motivation and job fit. Negatively, such AI systems' effective rollout and management (Vedapradha et al., 2023) is critical to their successful adoption. Organisations are more likely to adopt AI technologies that they believe are effective in improving recruitment processes. Potential benefits AI has produced in the talent acquisition process are presented below (Yadav et al., 2023). Perceived ease of use is the second major factor influencing its adoption. However, it is very hard for the user to decide how easily a system should use artificial intelligence. The Technology Acceptance Model, TAM, states that if a particular technology looks easy, it will likely be adopted by the users. User-friendly and light-loaded

AI tools that impose practically no effort on HR professionals are more commonly employed in talent acquisition (Damerji & Salimi, 2021). The perceived usefulness of AI technologies is another important factor affecting its adoption. HR practitioners value AI tools that deliver clear benefits, such as augmenting candidate similarity and intelligence, building a diverse team, and eliminating bias from the hiring process by providing them with what they seek in the AI community (Pillai & Sivathanu, 2020). Suppose AI systems are shown to be useful in meeting recruitment goals. In that case, organisations will implement those technologies more readily than if they believe human labor is the only way.

Competence is one of the key factors in implementing artificial intelligence in recruiting and making it functional. Organisations must validate the efficacy of their AI systems and HR professionals to ensure that they are competent in taking on more complicated recruitment functions. This data helps to predict what later competencies the candidates could possess: knowledge, motivation or scientific or professional behavior that may be necessary for organisational objectives. AI has been one of the key technological disruptions in HR because it helps gauge candidate competency and streamlines talent acquisition (Vedapradha et al., 2023) . AI augments talent acquisition by making processes like shortlisting resumes, scheduling interviews and conducting them more effective. While HR professionals are flagged for anything out of the ordinary and can go in directly to review a small number of candidates for full-time positions, this frees them up to spend more time on strategic work overall. Studies have found that using AI (Yadav et al., 2023) has been shown to increase efficiency in hiring by reducing the time taken to hire appropriate people and improving the candidate-job fit.The Technology Acceptance Model (TAM) posits that when AI tools are user-friendly and ease of use , it will foster HR teams to willingly use them. Further, increased ease of use is possible by enhancing the user experience and making AI tools more adaptable by talent acquisition (Venkatesh & Davis, 1996). Perceived usefulness also forms the list of essential factors in AI being adopted in recruitment processes. Candidates match and speed up the recruitment process, which are expected outcomes that AI tools deliver better, and the higher the chance they have to be integrated with talent acquisition workflows. Thus, the perceived usefulness of AI tools has an elaborative influence on HR professionals' intention to use these technologies, as one determinant is believed might lead to another and finally achieve a broader adoption of AI (Damerji & Salimi, 2021).

Competency is important in adopting and using AI for Talent Management. AI adoption significantly depends on the capabilities of HR professionals and AI systems to evaluate candidate competencies. For example, AI-powered tools that assess candidate competencies using multiple lenses (knowledge, skills, and job fit) allow smarter talent management decisions. We can see in the IT industry that AI systems adoption gets higher as long we are using competency (Vedapradha et al., 2023).AI streamlines numerous time-consuming talent management processes, like screening, interviewing, and candidate matching. How it Works The perceived effectiveness of these AI systems positively influences their adoption and usage, which are expected. Companies witness a more efficient and accurate method of hiring when they have better recruitment outcomes due to effective AI systems that ultimately promote talent management (Yadav et al.,2023). The ease with which AI systems can be used mediates the adoption of AI in talent management. Whether AI tools are intuitive and easy to implement makes a significant difference in whether HR professionals will find them accessible during recruitment. The Technology Acceptance Model (TAM) supports the proposition that easier-to-use systems will more likely be integrated into organisational routines (Gefen & Straub, 2000). Support for this easy usage allows Companies to automate huge parts of the tasks and, therefore, is a crucial ingredient in making AI work on the HR side. The more the perceived usefulness, the greater the chance of adoption and using AI in talent management. HR professionals are more inclined to adopt AI when they appreciate how it is a useful tool that enhances recruitment outcomes. The systems that organisations learned to use AI, if found useful or advantageous, would also help make more strategic talent management decisions by becoming more efficient and correcting biases in selecting candidates (Damerji & Salimi, 2021).

While there is a burgeoning body of literature on the impact of AI on talent acquisition globally, a large gap still exists in our understanding of how AI influences talent acquisition, specifically in regional contexts, especially within North East India. While much of the existing literature is limited to large technology-driven urban centres, with a focus on tribal societies like North East India, where HR practices would differ due to largely small-level industries and less technologically sound infrastructure and a diverse workforce further highlights an area that should have merited attention and requires unique Policy Initiatives.

## 2.1 Competency

AI is also relevant in the improvement of the competency of HR professionals in the management of talent acquisition tasks. Rukadikar et al. (2023) note that AI helps match skills, profile candidates, and simplify recruitment processes, so that the HR professionals will be able to handle more candidates with greater efficiency. With AI-assisted applications such as resume screening and predictive analytics, the competency of the talent acquisition team can be enhanced because they automate repetitive tasks and deliver data-driven insights (Reddy et al., 2025). However, the competency of AI systems themselves depends on the algorithms' quality, requiring HR professionals to continually adapt to new AI technologies to effectively utilise them (Kadirov et al., 2024).

## 2.2 Effectiveness

The success of AI in talent acquisition is realised in a number of ways. Research indicates that AI is an effective way of improving recruitment results because it lowers time-to-hire and increases the quality of the hires. The sourcing of candidates and initial screenings by using AI can be more objective and reduce human biases (Vedapradha et al., 2023). In addition, the use of AI, such as chatbots and machine learning algorithms, results in a more proficient and accurate match of candidates (Yadav et al., 2023). The efficiency of operations is enhanced by the capability of AI to automate the time consuming activities, and this frees up the HR professionals to concentrate on strategic decisions, thereby enhancing the effectiveness of the entire recruitment process.

## 2.3 Usability

The user-friendliness of the AI tools is vital towards the successful implementation of AI tools in talent acquisition. User-friendly AI systems that have an intuitive interface can be more easily integrated into HR's working processes. According to Rukadikar et al. (2023), the ease of use is the primary factor that encourages the use of AI in India and especially in IT firms, because the systems do not need much technical knowledge on the part of HRs. Ease of use also correlates with the technology acceptance model, where HR professionals' positive attitudes towards AI are shaped by their perceived ease of interaction with the tools (Fatin, 2025). The simpler the technology can be implemented and utilised, the more chances that it will be accepted and adopted into the HR practices (Alnsour et al., 2024).

## 2.4 Usefulness

The perceived usefulness of AI in talent acquisition is one of the main factors that determine its adoption. As it was shown by Reddy et al. (2025), AI has also increased the perceived usefulness of talent acquisition by largely improving the candidate experience, a major determinant of the success in the recruitment process. Moreover, the capability of AI to provide predictive analysis of candidate performance, workforce trends, and attrition rates will be of great use to the HR decision-makers (Kadirov et al., 2024). AI enhances hiring process effectiveness as well, because it offers data-driven insights, proving the HR to be more valuable to the organisations as a strategic asset. In North East India, where HR functions may still be evolving, AI's usefulness is becoming increasingly evident as it offers solutions to challenges like talent shortages and biases in traditional recruitment practices (Ibrahim & Hassan, 2019).

Further, existing research on AI adoption in recruitment has mainly discussed competency, effectiveness, perceived ease of use and perceived usefulness separately without understanding how these determinants influence or mediate the entire process and usage of such innovation, specifically in the context of HR sectors in North-East India. Even less is known about how these dimensions affect the role of AI in addressing regional challenges, such as skill shortages, industrial demands, and HR operational skills.

Therefore, there is an imperative requirement for a study in the local context to understand the competency, effectiveness, ease of use and usefulness of AI as technology volatile talent acquisition processes within North East India's HR sectors. Fulfilling this gap can provide a holistic view for academia and practitioners to design region-specific AI-driven solutions.

This paper underscores the crucial role of AI users in maximising the potential of AI. It concludes that specific adaptation of training programs is necessary to ensure that users are equipped with the skills needed to effectively leverage AI. The research will also contribute to the global discourse on AI in HR by highlighting the conditions that influence AI adoption in emerging economies. Rooted in health systems, sectors, and broader contextual complexities, this research could serve as a model for other regions facing similar challenges and provide valuable insights for international entities seeking to tailor their AI strategies to specific regional contexts. In this context, the study has the following objectives:

- To assess the skills needed for integrating AI into HR practices, especially managing employee lifecycles.
- To examine the gap between AI's perceived and actual impact on recruitment outcomes.
- To explore the usability and effectiveness of AI tools for HR professionals in talent acquisition.
- To offer recommendations for improving AI-driven talent acquisition in organisations in North East India.

The study has set the following hypotheses for testing:

**Hypothesis 1:** The application of AI positively impacts Talent Acquisition process.

**Hypothesis 2:** Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness impact the adoption and actual usage of AI in Talent Acquisition.

**Hypothesis 2a:** Competency impacts the adoption and actual usage of AI in Talent Acquisition.
**Hypothesis 2b:** Effectiveness influences the adoption and actual usage of AI in Talent Acquisition.
**Hypothesis 2c:** Perceived Ease of Use affects the adoption and actual usage of AI in Talent Acquisition.
**Hypothesis 2d:** Perceived Usefulness impacts the adoption and actual usage of AI in Talent Acquisition.
**Hypothesis 3:** Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness impact Talent Acquisition process.
**Hypothesis 3a:** Competency impacts in Talent Acquisition process.
**Hypothesis 3b:** Effectiveness influences in Talent Acquisition process.
**Hypothesis 3c:** Perceived Ease of Use affects in Talent Acquisition process.
**Hypothesis 3d:** Perceived Usefulness impacts in Talent Acquisition process.
**Hypothesis 4:** The adoption & actual usage mediate the effect of Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness on Talent Management.

## 3. Research Methodology

### 3.1 Research Design

This study employs a quantitative research approach, utilising a survey methodology to examine the impact of AI on personnel recruitment. We opted for a survey to gather comprehensive feedback regarding HR professionals' views and encounters with AI in their hiring processes. This method facilitates the collection of substantial data, which is essential for conducting a statistically robust analysis.

## 3.2 Sampling Plan

A study has been undertaken in North-Eastern India, focusing on HR professionals engaged in talent acquisition across various industries, including IT, Power Distribution, FMCG, and Healthcare. The survey collected responses using random sampling and Google Form from more than 328 HR professionals, aiming to provide a comprehensive and varied sample that demonstrates the impact of AI on talent acquisition within this geographical region.

## 3.3 Materials and Equipment

The data analysis and examination of research hypotheses are conducted using SPSS 29 and AMOS 24 software packages.

## 3.4 Experimental Procedures

Data is usually collected by following several important steps:
Development of the Survey: A comprehensive questionnaire containing validated scales to assess competency, effectiveness, perceived ease of use and usefulness of AI in recruiting is established. It also includes demographic questions so the surveyor understands who is completing this form better.

**Pilot Testing:** A small group of HR professionals is asked to complete the questionnaire to assess the clarity of survey questions and reliability. The pilot study was done to ascertain the clarity and reliability of the survey that was applied in this research. The survey was done on a small sample of 30 HR professionals in North-East India who gave their feedback on wording, structure, and time it takes to complete the survey. On this basis, the survey was revised to make it better. Reliability analysis using Cronbach's alpha showed excellent internal consistency across all factors (0.967 to 0.972), and factor analysis confirmed the suitability of the data for further analysis, with a KMO value of 0.937 and significant Bartlett's Test of Sphericity ($p < 0.001$). This pilot study made the final survey to be reliable and valid in the data collection.

**Administration of survey:** An email with a link to the finalised questionary is sent out to the chosen sample, and participants are given around two weeks to respond.

**Data Collection:** The online platform ensures that responses are collected in a manner that protects data integrity while maintaining confidentiality.

## 3.5 Data Analysis

The data is analysed by SPSS (Statistical Package for Social Science) version 29. Descriptive statistics calculate the demographic characteristics of the sample. With multiple regression and correlation, hypothesis testing is carried out to test the impact of competency, effectiveness, perceived ease of use and usefulness on AI adoption and talent acquisition process. In the second section, Mediation analysis is administered to measure the mediating effect of AI adoption and usage on independent factors with talent management outcomes. This is performed with AMOS 24 software.

## 3.6 Quality Controls and Assurances

Each of the following measures has been implemented to ensure the validity and reliability of the results:

Pilot Testing: Pilot testing of the survey instrument is conducted to help address problems with question wording or structure.

Reliability analysis: Cronbach's alpha is computed to test the internal consistency of each scale.

Validity: Content validity is guaranteed by expert reviews of the survey questions. Factor analysis is used for construct validity.

Cleaning data: Raw data is reviewed to remove incomplete or irrelevant answers.

## 3.7 Statistical Assumptions

To ensure the appropriateness of statistical techniques, it is essential to verify assumptions such as normality, linearity and homoscedasticity when conducting regression analysis. We used histograms to verify the distribution of the residuals in order to test the normality. Scatter plots were used to investigate the correlation between independent and dependent variables, which is linearity. Lastly, the test by White was used to test the homoscedasticity in that the residual variance was to be constant across all the levels of the independent variables. Our regression models were validated with the help of these diagnostic procedures.

## 4. Data Analysis

The research encompassed 328 human resources professionals from various industries in North East India, offering a comprehensive view of the sample's demographic profile. This information is crucial when considered alongside the study itself, as it illustrates the potential impact of artificial intelligence on talent acquisition.

**Table 1: Demographic profile of respondents**

| **Age** | | | | | |
|---|---|---|---|---|---|
| | | **Frequency** | **Percent** | **Valid Percent** | **Cumulative Percent** |
| **Valid** | 20-30 | 81 | 24.7 | 24.7 | 24.7 |
| | 31-40 | 91 | 27.7 | 27.7 | 52.4 |
| | 41-50 | 68 | 20.7 | 20.7 | 73.2 |
| | 51-60 | 88 | 26.8 | 26.8 | 100.0 |
| | Total | 328 | 100.0 | 100.0 | |
| **Gender** | | | | | |
| | | **Frequency** | **Percent** | **Valid Percent** | **Cumulative Percent** |
| **Valid** | Male | 229 | 69.8 | 69.8 | 69.8 |
| | Female | 99 | 30.2 | 30.2 | 100.0 |
| | Total | 328 | 100.0 | 100.0 | |
| **Experience** | | | | | |
| | | **Frequency** | **Percent** | **Valid Percent** | **Cumulative Percent** |
| **Valid** | 1-10 Years | 82 | 25.0 | 25.0 | 25.0 |
| | 11-20 Years | 94 | 28.7 | 28.7 | 53.7 |
| | 21-30 Years | 107 | 32.6 | 32.6 | 86.3 |
| | 31-40 Years | 45 | 13.7 | 13.7 | 100.0 |
| | Total | 328 | 100.0 | 100.0 | |
| **Education Level** | | | | | |
| | | **Frequency** | **Percent** | **Valid Percent** | **Cumulative Percent** |
| **Valid** | MBA | 243 | 74.1 | 74.1 | 74.1 |
| | MCom | 78 | 23.8 | 23.8 | 97.9 |
| | PhD | 7 | 2.1 | 2.1 | 100.0 |
| | Total | 328 | 100.0 | 100.0 | |

Source: Author's collection.

The survey respondents' ages were distributed as follows: 24.7% were 20-30 years old, 27.7% were 31-40 years old, 20.7% were 41-50 years old, and 26.8% were between 51 and 60 years old. Table 1 illustrates a wide range of ages from under 30 to 60, suggesting a diversity of experiences and perspectives among HR professionals. The second-largest group, comprising 26.8% of the sample, was the 51-60 age bracket. This well-balanced distribution offers a comprehensive insight into how AI impacts individuals at various stages of their careers.

One of the most notable aspects of this survey is the gender distribution in Table 1, which includes 69.8% male and only 30.2% female respondents. This signifies that this is a male-majority sample, resonant with the locality's overarching HR professional demographic. As a profession that employs more men than any other white-collar field, a higher percentage of male HR practitioners could be shaping the views around AI adoption and utilisation, which may shed light on some of the gender-specific obstacles and advantages in talent acquisition.

For Professional experience in table-1, the total count was as follows: 25.0% experienced 1–10 years, 28.7% experienced 11–20 years,32.6% experienced 21–30 years, and13.8% experienced 31–40 years. Cumulatively, more than three-fifths of the respondents (61.3%) have 11–30 years of HR experience, suggesting a sample with considerable professional heritage and capability in their chosen discipline. This wealth of experience is essential for making accurate judgments about AI's relative value and feasibility in talent acquisition.

The educational background in table -1 of the respondents reveals that 74.1% are MBAs, 23.8% MComs, and only 2.1% hold a PhD. The large number of MBA holders implies a good level of overall managerial and business training among the HR professionals, which is important to consider when evaluating these masterminds' competence and readiness for deploying AI technologies. This small proportion of PhD holders is consistent with the emphasis on practical experience in this study and professional rather than more academic degrees held by most respondents.

**Table 2: KMO and Bartlett's Test**

| **Test Statistics** | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .937 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 25651.589 |
| | df | 2415 |
| | Sig. | <.001 |

Source: Author's collection.

Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity in Table 2 provide important information based on data collected from HR professionals in North East India, specifically regarding the impact of AI on talent acquisition. The KMO value is 0.937, which means the sample was adequately large. Values near 1.0 indicate that the data is appropriate for factor analysis. Bartlett's Test of Sphericity also supports this appropriateness with an approx. Chi-square value of 25,651.589, degrees of freedom (df) = 2,415 and Sig. of less than 0.001. This result is meaningful as it indicates strong enough correlations among the items to conduct a factor analysis.

**Table 3: Rotated Component Matrix**

| **Component Matrix**[a] | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
|---|---|---|---|---|---|---|---|
| TA10 | .907 | | | | | | |
| TA5 | .906 | | | | | | |
| TA8 | .897 | | | | | | |
| TA7 | .896 | | | | | | |
| TA3 | .887 | | | | | | |
| TA6 | .883 | | | | | | |
| TA4 | .882 | | | | | | |
| TA9 | .881 | | | | | | |
| TA1 | .877 | | | | | | |
| TA2 | .876 | | | | | | |
| EU9 | | .901 | | | | | |
| EU7 | | .901 | | | | | |
| EU2 | | .897 | | | | | |
| EU1 | | .896 | | | | | |
| EU6 | | .892 | | | | | |
| EU8 | | .891 | | | | | |
| EU3 | | .889 | | | | | |
| EU4 | | .876 | | | | | |
| EU5 | | .870 | | | | | |
| EU10 | | .869 | | | | | |

| Component Matrix[a] | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| AAU3 | | | .899 | | | | |
| AAU1 | | | .897 | | | | |
| AAU5 | | | .897 | | | | |
| AAU6 | | | .895 | | | | |
| AAU10 | | | .890 | | | | |
| AAU9 | | | .889 | | | | |
| AAU7 | | | .883 | | | | |
| AAU2 | | | .880 | | | | |
| AAU4 | | | .872 | | | | |
| AAU8 | | | .869 | | | | |
| U7 | | | | .901 | | | |
| U2 | | | | .901 | | | |
| U6 | | | | .891 | | | |
| U4 | | | | .891 | | | |
| U1 | | | | .890 | | | |
| U10 | | | | .887 | | | |
| U3 | | | | .882 | | | |
| U9 | | | | .882 | | | |
| U8 | | | | .874 | | | |
| U5 | | | | .867 | | | |
| C5 | | | | | .902 | | |
| C4 | | | | | .899 | | |
| C10 | | | | | .896 | | |
| C6 | | | | | .885 | | |
| C2 | | | | | .884 | | |
| C7 | | | | | .884 | | |
| C9 | | | | | .881 | | |
| C1 | | | | | .881 | | |
| C8 | | | | | .880 | | |
| C3 | | | | | .876 | | |
| AAA5 | | | | | | .898 | |
| AAA10 | | | | | | .896 | |
| AAA3 | | | | | | .889 | |
| AAA9 | | | | | | .887 | |
| AAA7 | | | | | | .884 | |
| AAA8 | | | | | | .881 | |
| AAA6 | | | | | | .876 | |
| AAA1 | | | | | | .872 | |
| AAA2 | | | | | | .868 | |
| AAA4 | | | | | | .860 | |
| E2 | | | | | | | .899 |
| E8 | | | | | | | .887 |
| E6 | | | | | | | .884 |
| E4 | | | | | | | .882 |
| E5 | | | | | | | .881 |
| E10 | | | | | | | .874 |
| E1 | | | | | | | .873 |
| E3 | | | | | | | .864 |
| E7 | | | | | | | .860 |
| E9 | | | | | | | .855 |

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

Source: Author's calculation.

Results show seven components based on the Rotated Component Matrix, which was obtained by applying Principal Component Analysis with Varimax rotation to explain the variance in data. Different factors within survey data are represented as components, and items load strongly on certain components.

**Table 4: Total Variance Explained**

| Component | Rotation Sums of Squared Loadings | | |
|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** |
| 1 | 8.016 | 11.452 | 11.452 |
| 2 | 8.007 | 11.439 | 22.890 |
| 3 | 7.953 | 11.362 | 34.252 |
| 4 | 7.945 | 11.350 | 45.601 |
| 5 | 7.941 | 11.344 | 56.946 |
| 6 | 7.863 | 11.233 | 68.178 |
| 7 | 7.734 | 11.048 | 79.227 |

Extraction Method: Principal Component Analysis.

Source: Author's calculation.

The combined variance in table-4 accounted for by the seventh component is substantial. The first component tells you 11.452% of the variance, whereas the second component will have something like 11.439%. For instance, for the third, fourth, fifth, sixth and seventh components, they explain 11.362%, 11.350%, 11.344%, 11.233% and 11.048% of variance accordingly. Together, these components explain 79.227% of the total variance, which suggests a stable factor structure and accounts for high common covariance.

**Table 5: Reliability Statistics of different factors**

| Reliability Statistics | | |
|---|---|---|
| **Factors** | **Cronbach's Alpha** | **No. of Items** |
| **AI Application Awareness** | 0.969 | 10 |
| **Competency** | 0.970 | 10 |
| **Effectiveness** | 0.967 | 10 |
| **Ease of Use** | 0.971 | 10 |
| **Usefulness** | 0.971 | 10 |
| **Adoption** | 0.972 | 10 |
| **Talent Acquisition** | 0.971 | 10 |

Source: Author's calculation.

The survey tools in this study were evaluated for their reliability by Cronbach's Alpha, which tests the consistency of the survey items. A high Cronbach's Alpha value indicates that the questions inside a factor are related to one another and that these answer the same question, proving that the survey items measure what they intended to provide.

**AI Application Awareness:** This factor has a Cronbach's Alpha of 0.969, suggesting an optimal consistency.
**Competency:** "Competency" is also highly reliable (Cronbach's Alpha = 0.970). This indicates that the 10 questions used to survey respondents' AI talent acquisition competence are reliable.
**Effectiveness:** The Cronbach's Alpha is 0.967, suggesting high reliability of the measure on a scale from 1 to 10 for both "Effectiveness" factors.
**Ease of Use:** The Cronbach's Alpha of the "Ease of Use" factor gets 0.971, which also shows excellent reliability.
**Usefulness:** Also, the "Usefulness" factor has high reliability (Cronbach's Alpha: 0.971). The 10 questions that gauge the utility of AI in hiring are therefore reliable- they provide an accurate measure consistently.
**Adoption:** The most consistent section in the questions of AI tool usage and adoption with Cronbach's Alpha 0.972:

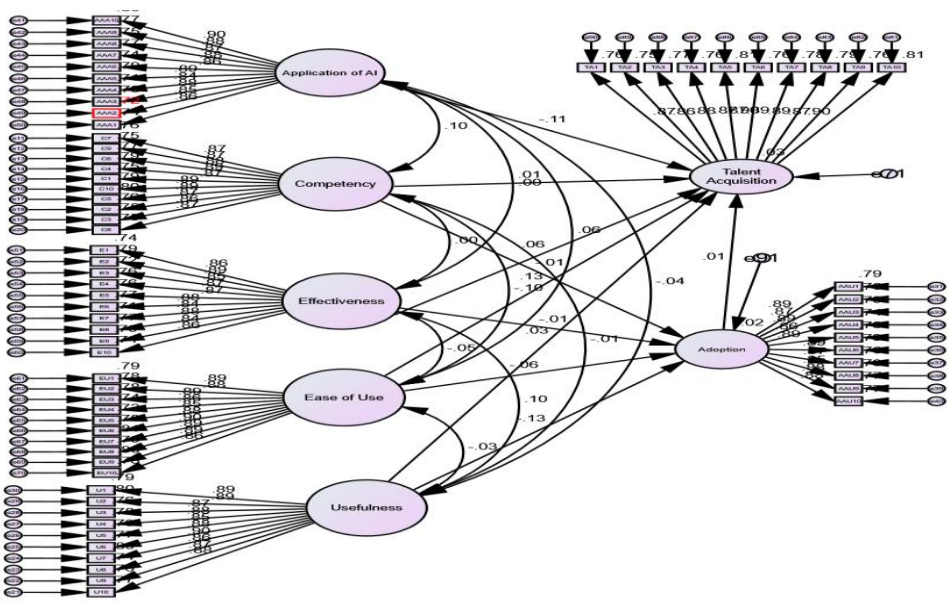


**Figure 1: Structural Equation Model**

**Table 6: Model Fit Measures**

| Measure | Estimate | Threshold | Interpretation |
|---|---|---|---|
| CMIN | 2452.273 | -- | -- |
| DF | 2325.000 | -- | -- |
| CMIN/DF | 1.055 | Between 1 and 3 | Excellent |
| CFI | 0.995 | >0.95 | Excellent |
| SRMR | 0.033 | <0.08 | Excellent |
| RMSEA | 0.013 | <0.06 | Excellent |
| PClose | 1.000 | >0.05 | Excellent |

Source: Authors' calculation.

The CMIN value (Chi-Square) is 2452.273, with a DF of 2325 corresponding to the model. The value of DF (degrees of freedom) 2325.000 indicates the number of independent values or parameters which can vary in the statistical model. It is applied in computing chi-square statistic (CMIN) that determines model fit. The larger the DF, the more complex the model and the more variables or data points, which implies that the model can account variance in the data. The DF of 2325 in this study shows the complexity of the model to be utilised in analysing data of North East Indian HR professionals. Although Chi-Square alone can sometimes be sensitive to sample size and may not always provide the best indication, the CMIN/DF, where CMIN is the goodness of fit statistics term compared to DF, helps with this.

The CMIN/DF Ratio (1.055 is very good, with the ideal range being between 1 and 3). It indicates that the model complexity and data are well-defined; hence, it does a great job representing the relationships in the study.

According to the CFI value of 0.995, This is also more than the minimum threshold of 0.95 recommended in the literature37 38. This corresponds to a model doing a very good job fitting the data, significantly better than the baseline (or starting) model.

The SRMR value is 0.033, well below the recommended maximum of 0. That is a good fit since SRMR measures the discrepancy of real vs. expected values; thus, smaller denotes a better fit.

The RMSEA is 0.013, comfortably below the accepted cut-off value of 0.06. This means that the model fits the underlying data structure extremely well.

The PClose, as evidenced by 1.000, is much higher than the suggested minimum value of 0,05. This is a test to see if RMSEA is small enough, and PClose is higher, which means a better fit of the model.

The model fit measures indicate that the proposed evaluation framework to measure the Impact of AI in Talent Acquisition is excellent. Results are in recommended ranges, suggesting a well-fitting model that accurately represents the data and relationships being investigated. It is critical to note that these analyses were conducted within a single strong model fit construct, confirming the validity and reliability of our findings on AI event (1) influencing competence, effectiveness, ease-of-use and utility in talent acquisition.

The goodness of fit statistics shows that the model fits well with the data; the model fit indices, including CMIN/DF (1.055), CFI (0.995), SRMR (0.033), and RMSEA (0.013), indicate that the model is an excellent fit. This large fit shows that the constructs that are being measured (e.g., competency, effectiveness, ease of use, and usefulness) have good representations in the model and therefore construct validity. The model shows that variables are related as the hypothesised and the indices are validating the constructs. While the provided table-6 doesn't directly provide information to assess discriminant validity (such as cross-loadings in factor analysis or Average Variance Extracted (AVE) comparisons), the high CFI and low RMSEA values imply that the model differentiates between constructs effectively. An adequate model will be less likely to overlap constructs, which indirectly supports discriminant validity, because it implies that constructs are not too similar.

**Hypothesis 1:** The application of AI positively impacts Talent Acquisition process
**Hypothesis 2:** (a) Competency, (b) Effectiveness, (c) Perceived Ease of Use and (d) Perceived Usefulness impact the adoption & actual usage of AI in Talent Acquisition
**Hypothesis 3:** (a) Competency, (b) Effectiveness, (c)Perceived Ease of Use and (d) Perceived Usefulness impact Talent Acquisition process.

**Table 7: Standardised Regression Weights of Model**

**Standardised Regression Weights: (Group number 1 - Default model)**

| Parameter | | | Estimate | Lower | Upper | P | Interpretation |
|---|---|---|---|---|---|---|---|
| Adoption and Actual Usage | <--- | Competency | -0.009 | -0.123 | 0.106 | 0.869 | H2a = Rejected |
| Adoption and Actual Usage | <--- | Ease of Use | -0.06 | -0.172 | 0.048 | 0.259 | H2c = Rejected |
| Adoption and Actual Usage | <--- | Usefulness | -0.132 | -0.243 | -0.015 | 0.027 | H2d = Accepted |
| Adoption and Actual Usage | <--- | Effectiveness | -0.008 | -0.121 | 0.102 | 0.881 | H2b = Rejected |
| Talent Acquisition | <--- | Application AI | -0.109 | -0.223 | 0.008 | 0.067 | H1 = Rejected |
| Talent Acquisition | <--- | Competency | 0.006 | -0.11 | 0.121 | 0.922 | H3a = Rejected |
| Talent Acquisition | <--- | Effectiveness | 0.056 | -0.044 | 0.167 | 0.27 | H3b = Rejected |
| Talent Acquisition | <--- | Ease of Use | 0.132 | 0.021 | 0.244 | 0.026 | H3c = Accepted |
| Talent Acquisition | <--- | Usefulness | 0.027 | -0.075 | 0.142 | 0.598 | H3d = Rejected |

Source: Authors' calculation.

**Table 8: Squared Multiple Correlations of Model**

| Parameter | Estimate | Lower | Upper | P |
|---|---|---|---|---|
| Adoption | .021 | .001 | .044 | .038 |
| Talent Acquisition | .031 | | .055 | .094 |

Source: Authors' calculation.

**Hypothesis 1:** The use of AI impacts talent acquisition efficiency positively.

The data presented in this table indicates that the standardised regression coefficient for the impact of AI on talent acquisition is -0.109, with a corresponding p-value of 0.067. Given that this p-value exceeds the conventional significance threshold of 0.05, we are compelled to dismiss hypothesis $H_1$.

Consequently, within this particular sample, the findings suggest that AI does not exert a statistically significant positive influence on the process of talent acquisition.

**Hypothesis 2:** (a) Competency, (b) Effectiveness, (c)Perceived Ease of Use, and (d) Perceived Usefulness impact the adoption & actual usage of AI in Talent Acquisition

The effect of competency on AI adoption has a regression weight of -0.009 (p = 0.869); thus, Hypothesis 2a is also rejected.

The regression weight for the impact of Ease of Use on AI adoption is -0.060 (p = 0.259); therefore, Hypothesis 2c was also rejected.

Its usefulness greatly affects adoption, and the regression weight is -0.132 (p = 0.027). As such, Hypothesis 2d (based on the Perceived Usefulness of AI) is supported, demonstrating that the more useful AI solutions are perceived to be in recruitment processes, the more liable companies will opt to adopt these within a chosen talent acquisition function.

Contrary to the hypothesised positive relationship between AI adoption and effectiveness, the regression weight for effectiveness on AI adoption was -0.008 (p = 0.881), which led to a rejection of Hypothesis 2b.

**Hypothesis 3** : Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness directly affect the talent acquisition process.

Hypothesis 3a, relating to competency influence on talent acquisition, is not supported as the weight of its regression coefficient is 0.006 (p = 0.922).

No support was found for Hypothesis 3b with the non-significant regression weight of Effectiveness on talent acquisition (0.056, p = 0.270).

In the case of Talent acquisition, ease of use also has a positive and significant effect with the regression weight 0.132 (p = 0.026). Thus, Hypothesis 3c is supported, suggesting that perceptual ease of use supremely affects the talent acquisition process.

Hypothesis 3d is also rejected because the regression weight of usefulness for talent acquisition is insignificant (0.027, p = 0,598).

R-Square values indicate the proportion of variations in outcomes that are explained by factors included in the model

The R-Square value for AI adoption is 0.021, indicating that only 2.1% of the variance in AI adoption behaviour can be explained by competency, effectiveness, perceived ease of use, and perceived usefulness. This could mean that others can have a larger impact on AI adoption.

We find a low value of the R-Square for talent acquisition (0.031), suggesting that AI and adoption factors explain only 3.1% of the variation in talent acquisition. This indicates that further variables need to be taken into account to get a thorough understanding of the effect on Talent Acquisition.

**Hypothesis 4:** The adoption & actual usage mediate the effect of Competency, Effectiveness, Perceived Ease of Use and Perceived Usefulness on Talent Management.

**Table 9: Impact of Competency, Effectiveness, Perceived Ease of Use, and Perceived Usefulness on Talent Management Outcomes**

| Parameter | | Estimate | Lower | Upper | P | Interpretation |
|---|---|---|---|---|---|---|
| **Indirect Effect** | | | | | | |
| **Ind1** | Competency to Talent Acquisition Via Adoption | 0 | -0.01 | 0.007 | 0.841 | H4ai=Rejected |
| **Ind2** | Effectiveness to Talent Acquisition Via Adoption | 0 | -0.011 | 0.007 | 0.774 | H4bi=Rejected |
| **Ind3** | Perceived Ease of Use to Talent Acquisition Via | -0.001 | -0.017 | 0.006 | 0.577 | H4ci=Rejected |

| Parameter | | Estimate | Lower | Upper | P | Interpretation |
|---|---|---|---|---|---|---|
| | Adoption | | | | | |
| **Ind4** | Perceived Usefulness to Talent Acquisition Via Adoption | -0.002 | -0.024 | 0.013 | 0.706 | H4di=Rejected |
| **Total Effect** | | | | | | |
| **TInd1** | Total Effect of Competency to Talent Acquisition Via Adoption | 0.006 | -0.119 | 0.13 | 0.916 | H4aii=Rejected |
| **TInd2** | Total Effect of Effectiveness to Talent Acquisition Via Adoption | 0.063 | -0.051 | 0.184 | 0.279 | H4bii=Rejected |
| **TInd3** | Total Effect of Perceived Ease of Use to Talent Acquisition Via Adoption | 0.136 | 0.022 | 0.251 | 0.025 | H4cii=Accepted |
| **TInd4** | Total Effect of Perceived Usefulness to Talent Acquisition Via Adoption | 0.026 | -0.08 | 0.145 | 0.63 | H4dii=Rejected |

Source: Authors' calculation.

The results revealed a non-significant indirect effect of 0, with a p-value of .841, indicating no substantial impact. Consequently, Hypothesis 4ai was not supported and thus dismissed. The results showed an indirect effect of 0 (p=0.774), suggesting no significant mediation. Consequently, Hypothesis 4bi is not supported. The indirect effect, with a value of -0.001 and a p-value of 0.577, was found to be statistically insignificant as a mediation effect. Consequently, the evidence does not support Hypothesis 4ci. The mediation effect lacks statistical significance, as evidenced by the indirect effect of -0.002 (p = 0.706). Consequently, we do not find support for Hypothesis 4di.

The overall effect is 0.006 (p = 0.916) of Competency to Talent Acquisition Via Adoption, indicating no statistically significant. Consequently, we do not accept Hypothesis 4aii.The total effect of Effectiveness to Talent Acquisition Via Adoption is 0.063, which yields p = 0.279, indicating that the total effect is not significant. Therefore, we fail to support Hypothesis 4bii. The Total Indirect Effect of Ease of Use on Talent Acquisition through Adoption is 0.136, with a p-value of 0.025, leading to the acceptance of hypothesis H4cii. The overall effect is 0.026 (p-value = 0.63), suggesting no substantial total impact. Consequently, Hypothesis 4dii is not supported.

## 5. Results and Discussion

The research findings indicated that neither AI systems' competency nor HR professionals' expertise had a statistically significant direct impact on the adoption of AI in talent acquisition. The standardised regression coefficient for competency exhibited the statistically lowest values of any (-0.009, p = 0.869), suggesting that whilst AI-driven recruitment did not demonstrate competence as crucial, it did not influence the adoption behaviour pattern in this study. This outcome can be attributed to a deficiency in technical training amongst HR professionals, highlighting the necessity for enhanced skill development prior to widespread implementation of AI systems.

The notion of perceived AI system efficacy did not significantly influence AI adoption rates. This rendered the hypothesis inconsequential, as we were unable to incorporate effectiveness as a direct predictor of AI utilisation in recruitment (regression weight -0.008, p = 0.881). It is conceivable that even if AI were to substantially enhance recruitment outcomes—which it has the capacity to do far more effectively than other software, as we have repeatedly emphasised over the years—this alone was insufficient to prompt a shift in usage at present.

The adoption of AI in talent acquisition was not primarily driven by its ease of use. The positive coefficient (β = +0.132; p=0.026) suggests that AI tools, which are more intuitive and simpler to implement are better integrated into HR practices. The willingness of HR professionals to utilise AI systems was significantly influenced by the user-friendliness of the AI technology during the period when adoption and usage were of interest. As anticipated, AI solutions that were more human-friendly and straightforward to deploy were more readily incorporated into HR processes.

The study also revealed that perceived usefulness significantly impacted AI adoption (regression weight = -0.132; p=0.027). This finding suggests that HR professionals were largely supportive of purpose-driven AI or AI for positive outcomes — implementing technology in areas where it could offer practical advantages, such as reducing bias, improving the match between candidates and jobs, or streamlining the recruitment process.

The analysis of mediation showed that the adoption and utilisation of AI acted as a mediator in the connection between ease of use and outcomes in talent acquisition. Specifically, the overall unreported mediation effect on talent acquisition was found to be 0.136 (p = 0.025). This finding suggests that as AI tools become more complex to use, human resources professionals face greater challenges in implementing effective talent acquisition strategies.

The R-squared values for AI adoption (0.021) and talent acquisition (0.031) indicate that, whilst ease of use and perceived usefulness impact these constructs, additional undiscovered or unexplored factors may also play a role. This finding suggests that additional research would be valuable to identify other factors influencing AI adoption, particularly within the North East Indian context.

In this study, the Hypothesis 2d (Perceived Usefulness) and Hypothesis 3c (Perceived Ease of Use) were accepted. Hypothesis 2d was validated with a significant negative regression coefficient (p = 0.027), and it was shown that the perceived usefulness has a positive effect on AI adoption. Equally, the Hypothesis 3c was accepted and the regression weight (beta = 0.132, p = 0.026) was significant indicating that ease of use is an important factor in improving the talent acquisition process.

These results emphasise the importance of ease of use and perceived benefits in relation to AI adoption and its eventual effect on talent acquisition. More generally, HR professionals preferred to use AI if the tools were simple or intuitive to ease in getting used to. This is indicative of a high hurdle caused by the sophistication of AI systems, hence, reducing these features could spark widespread adoption in HR practices. Second, the practical application AI has as a tool in areas of HR—such as its capacity to make sourcing more efficient without bias or improve matching between candidate and role—also determined whether these technologies were being implemented by different types of HR practitioners.

On the flip side, competency and effectiveness expected to have a major impact did not yield statistically significant effects on AI adoption or recruiting talent. While this points to the future potential of AI in HR, it also implies that possibly HR professionals in North East India are not yet technically equipped or trained in various aspects of AI thereby lowering the effectiveness of the technology. Also, AI tools might not yet be tuned to solve the unique problems of the HR sector in the region.

For AI to be effectively integrated into successful recruitment processes, HR professionals need solutions that are both efficient and user-friendly. This study reveals a significant gap between AI's potential and its practical implementation in business. Whilst global trends suggest AI has transformed HR practices, evidence from North East India presents a contrasting perspective. Moreover, although ease of use emerges as the primary factor driving AI adoption among this demographic, its apparent simplicity masks underwhelming results in terms of competency and effectiveness. This underscores a marked disparity between HR professionals' expectations of AI and the current capabilities available in the market.

The findings suggest that artificial intelligence can significantly enhance human resources practices when it aligns closely with the expertise of decision-makers and addresses local requirements. This research challenges the widespread belief that AI should be implemented uniformly across all contexts. Such a standardised approach may not be entirely appropriate, particularly in areas like North East India where technological infrastructure is limited.

The findings lend credence to the Technology Acceptance Model (TAM), which posits that perceived ease of use and perceived usefulness positively affect technology adoption. As initially noted by Venkatesh and Davis (1996) and recently corroborated by Damerji & Salimi (2021), systems that are inherently user-friendly are more likely to be integrated into routine organisational activities, a notion this study strongly confirms. Moreover, in line with Pillai & Sivathanu (2020) and earlier research, perceived usefulness emerges as a crucial factor in AI adoption for HR; organisations are more inclined to implement these tools when they recognise their utility!

Unlike previous research conducted in more developed and technologically advanced areas, this investigation suggests that competence and efficacy, despite being frequently emphasised in academic literature, may not be as crucial in regions with less mature technological infrastructure. Vedapradha et al. (2023) found that effectiveness is contingent upon the level of HR readiness and technological sophistication in a given area. The findings of this study corroborate this notion, emphasising that the impact of AI can be limited when there is insufficient skill or training to fully harness its capabilities.

## 6. Conclusion

The results of this research study underline the significance of contextualised knowledge and localisation of the implementation of Artificial Intelligence (AI) in talent acquisition especially in such a region as North East India. Although AI may provide considerable benefits in the efficiency of recruitment, the ease of use and the perceived usefulness of the AI tools are more valued by HR professionals in this region than technical competencies. This implies that organisations should emphasise on the simplification of AI systems and training programs to the HR professionals that will make them more competent in using the tools. To HR managers, embracing an AI that is easy to navigate, user-friendly and able to show tangible, immediate returns will be central to unlocking the full potential of AI-driven recruitment.

The significance of the study in context of literature is that it fills the knowledge gap about the adoption of AI in the context of North East India, which forms a socio-economic and cultural background. The analysis questions the wider, global view in which competency and effectiveness are the main forces behind the use of AI. Rather, it demonstrates that ease of use and perceived usefulness is more important. The future study is to explore further regional impacts that can influence the AI adoption, including access to infrastructure, social-cultural acceptance of AI in the HR process, and the changing nature of AI technologies across various industrial sectors. Furthermore, the investigation of the indirect effects of AI on the results of the talent acquisition, especially those covering diversity and inclusion, should be conducted.

The AI revolution in talent acquisition can lead to wide-ranging implications on society, especially to increase the inclusivity and minimise bias during the hiring process. With the increased use of AI tools in the region, they can change the traditional ways of recruitment which could have been based on gender, ethnic or socio-economic background biases. This may lead to the more diverse and equitable hiring. Nevertheless, the social adoption of AI will need to overcome the objections related to the issue of data privacy, the prospects of algorithmic bias, and the consequences of automation on employment. Policies ought to be made to make sure that AI technologies are applied in a responsible way especially in areas that lack advanced technological infrastructure.

The factors that contribute to the successful outcomes of AI in various industries and geographical areas and the transformation of the adoption behaviour of HR professionals over time, should be the areas of future studies. The paper indicates that the use of AI is low in North East India, but the increased attention to the perceived ease of use and utility could result in its increased implementation in the future. In this regard, there is a need to do longitudinal studies to understand the long-term effect of AI on recruitment practices, and talent management. In addition, the creation of region-specific AI tools to meet the needs of a particular region and sufficient training of HR professionals can improve the efficiency of AI implementation and help develop sustainable talent acquisition practices.

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Promoting Research

# Cointegration and Causality among BRICS Stock Markets during Covid-19 Crisis

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**Keywords**
ARDL; BRICS; Covid-19; Granger Causality; Johansen Cointegration.

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B23, C87, E44

**Abstract:** The BRICS nations-Brazil, Russia, India, China, and South Africa-represent significant emerging economies that have engaged in collaborative efforts in terms of trade, financial aid, and technical expertise despite their geopolitical differences. This study investigates the interconnectedness of these markets, particularly amid the global financial crisis triggered by the Covid-19 pandemic, based on their stock market data from October 24, 2019, to October 23, 2020. The research identifies causal links and long-term cointegration among the stock indices, by segregating the entire study period under three defined sub-periods: pre-crisis, crisis, and post-crisis. The indices examined include IBOVESPA (Brazil), MOEX (Russia), SENSEX (India), SSECI (China), and JTOPI (South Africa). Findings suggest that significant long-term co-movements among these markets predominantly occurred during the pandemic-induced crisis, with notable two-way causal relationships existing between the Indian market and both the South African and Russian markets. In the pre-crisis phase, the Indian market was influenced by the other two, while in the post-crisis transition, the only causal relationship noted involved the Indian market and Brazil. These insights may imply that Indian policymakers may strengthen economic ties with BRICS countries in the usual scenario. However, during global crises, exercising caution has been advised to mitigate potential spill-over effects.

## 1. Introduction

BRICS, an economic block comprising Brazil, Russia, India, China and South Africa, represents five major emerging economies of the world. Despite their Geopolitical diversity, these countries have collaborated with each other in trade openness, financial cooperation, and exchange of technical know-how by virtue of globalisation and growth in information and communication technology (Shahbaz et al., 2018). BRICS nations, barring Russia, have shown remarkable similarities in terms of their tendency to maintain a high amount of foreign reserves, a low level of cushioning against external debts, focus on the production of consumer goods, etc. (Movcham, 2015). All these factors have gone a long way towards building a sustainable economic integration among the BRICS nations. Naturally, an economic shock in one country resonates with the others through the channels of economic integration. Just before the Covid-19 pandemic, the real Gross Domestic Product (GDP) of the BRICS nations, on average, was growing at a rate of 2.48% (IMF, 2020).

In December 2019, in the Wuhan city of Hubei province, China, the first case of Covid-19 coronavirus disease (2019-nCov) was diagnosed. Soon after, World Health Organisation (WHO) declared it as a pandemic when the number of deaths from the virus crossed 20000. By then, China had controlled the outbreak to some extent. However, the centre of the Covid-19 pandemic has been shifted to emerging markets (Roy and Saha, 2020). By the end of August 2020, there had been a serious increase in the number of cases in Brazil and Russia. In India, the outbreak started at the end of March and, due to a high population density, the number of confirmed cases surged in no time

(Figure 1). As a measure of solution, the governments in BRICS countries have set a country-wide economic lockdown in motion (Ayittey et al., 2020). While it achieved its desired effect of capping the number of cases, the pandemic and its ensuing economic shutdowns resulted in stalled global trade and manufacturing production (John Hopkins University, 2020); reduction in domestic and export demand; decline in exchange rate; rising unemployment; and disruption in the supply chain network.

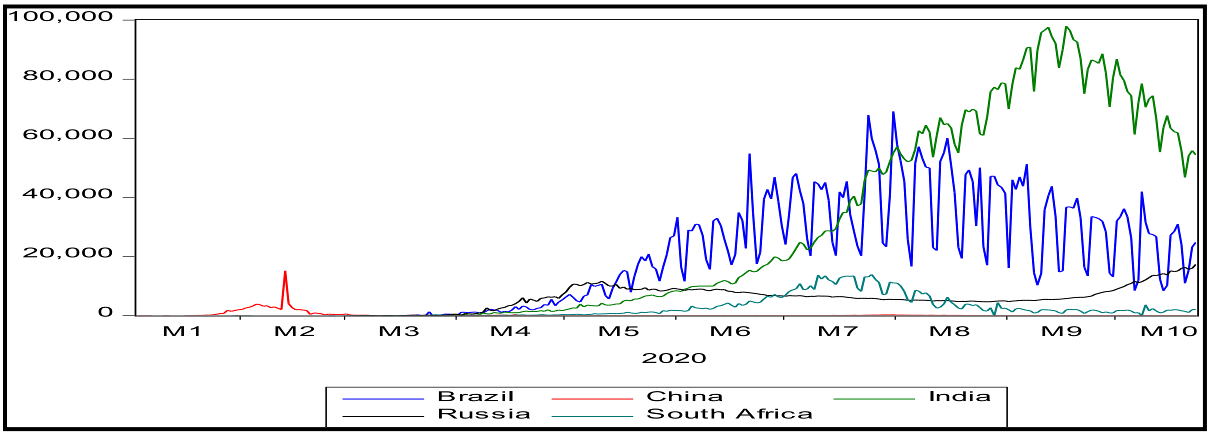


**Figure 1: Number of New Cases in BRICS Countries**

Source: Compilation of secondary data from WHO Covid Dashboard (WHO, 2020)

Since BRICS countries, especially China, had already proved their contribution to global growth, their struggle with the Covid-19 induced economic crisis hurt emerging market sentiments. However, China has showcased a strong capacity to fund proactive policy responses that contained the financial turmoil to some extent. Brazil, on the other hand, despite a strong healthcare system, ignored the impact of Covid-19 for a long time, which resulted in its economic collapse. Brazil, Russia being major oil exporters within BRICS, also faced a hit due to the Covid-19 induced oil price collapse. In countries like India and South Africa, meagre growth, high indebtedness, weak institutional capacity to mobilise fiscal or financial resources, huge social disparities, limited health infrastructure, and vulnerable informal groups limited their abilities to combat the crisis (Park and Garcia-Herreo, 2020). Covid-19 has exposed the faults in the administrative process in all five countries in navigating between health and economic priorities and its unavoidable impact on the livelihood of the common mass. However, even during this crisis, BRICS nations not only resorted to any hostile action against one another, but also have supported China and Russia when they became subject to the United States (US) confrontation on Covid-19 and subsequent vaccination issues, and US-China competition has become a focal point of international relations (Grigoryeva, 2020). Amid Covid-19, India too had entered into bilateral trade ties with other member countries (Rajagopalan, 2020) and jointly moved to the World Trade Organisation (WTO) to ease trade norms (The Hindu, 2020). However, India has recently gotten into several clashes with China (e.g. defence breach, banning of Chinese Apps, propaganda to disallow Chinese products, etc.), which may disrupt Sino-Indian economic relations in the future (Brar, 2020).

The stock market, being the barometer of economic performance in a country, signalled these economic vulnerabilities in BRICS countries (Mroua and Trabelsi, 2020). During February to June 2020, when Covid-19 was at its peak, stock markets went into an acute recession. In this backdrop, it becomes imperative to study whether the economic interconnectedness among the countries during the crisis has spilled over to their stock market relationships too.

In the stock market, black-swan theory (Taleb, 2010) is commonly used as a metaphor to designate an event which is highly unlikely as a black swan. It is used to describe the crises and financial turbulence that have come to the stock markets by shock and have large and harmful effects. In the last 20 years, the stock markets globally experienced multiple 'black-swan' events, such as the internet bubble burst (2001), sub-prime crisis (2007), leading to the global financial crisis (2008-09), European public debt crisis (2009), etc. These events have led to a deep depression in global stock prices and increased instability in the markets. Due to its increasing trend, policy makers and investor communities have placed greater attention on the long-run and short-run correlations among global stock markets, to prevent unwarranted volatility spill-over or to reap the benefit of portfolio diversification (Bekiros et al., 2017). Since countries under an economic block (e.g. BRICS, ASEAN, G7, G20, etc.) are interconnected by virtue of multilateral trade relations and other strategic partnerships, the effect of a black-swan is significantly felt in their stock markets. Covid-19 and its immediate economic aftershock had an unprecedented effect on global stock markets, especially the stock markets of BRICS nations. Since India is economically interconnected with its foreign counterparts under BRICS through multilateral trade ties and other strategic collaborations, stock market recession in one country is likely to spill over to other countries, leading to a stock market slump there as well. However, it would happen only if the BRICS stock markets are integrated in the long-run and a causal relationship exists among them, specifically during times of crisis. It would also limit the benefits of cross-country portfolio diversification for international investors.

The present study has attempted to address the following research questions:

(a) Were the BRICS stock markets integrated in the long run just prior to the Covid-19 led global financial crisis?
(b) Were the BRICS stock markets integrated in the long run during the Covid-19 led global financial crisis?
(c) Were the BRICS stock markets integrated in the long run in the transition period after the Covid-19 led global financial crisis?
(d) Were there any causal relationships among the BRICS stock markets just prior to the Covid-19 led global financial crisis?
(e) Were there any causal relationships among the BRICS stock markets during the Covid-19 led global financial crisis?
(f) Were there any causal relationships among the BRICS stock markets in the transition period after the Covid-19 led global financial crisis?

## 2. Review of Literature

Policymakers and investors have always been interested in the economic ties between various economic groups, such as the G7, BRICS, and the Organisation for Economic Cooperation and Development (OECD). Previous research demonstrated that in OECD nations, there were significant causal relationships between economic growth, inflation, and stock markets (Pradhan et al. 2015). Over the past ten years, the US and BRICS have shared a commercial partnership. Due to their trading connections, the US and BRICS economies were seen to partially integrate during the global financial crisis. The Standard and Poor's (S&P) 500, which represents the US stock market, experienced a financial shock that had a major impact on the stock returns in China, South Africa, and Brazil. Strong economic integration between the US and BRICS countries is what caused the conflict (Singh and Singh, 2016; Jin and An, 2016).

Stock market movements in BRICS and other emerging economies were found to be vulnerable to volatilities in select macro-economic variables, such as gold price, oil price, foreign exchange rate, etc. In one of the studies, a time-varying asymmetric dependence structure between gold and stock prices in the emerging markets had been identified (Bekiros, et al., 2017). It showed that gold often acted as a means of risk diversification for stock market investors in emerging economies (Raza, et al., 2016). However, the associated volatilities of gold and oil prices were found to have negative impact on the stock market returns. Since gold and oil were among India's top imported commodities, studies suggested that future volatilities in their prices might affect inflation and India's stock market sentiments. Furthermore, gold and oil prices at the international markets and Indian stock market returns were observed to be cointegrated with non-linear bi-directional causality between them. Implied volatilities of gold and oil prices were found to have positively impacted the implied volatility of Indian stock market returns (Bouri, et al., 2017). The studies also showed that despite projecting a high growth rate, BRICS economies were susceptible to the fluctuations in external shocks, especially in gold and oil prices. However, when it came to the impact of foreign exchange rates on stock returns, especially during the global financial crisis, it was observed that volatilities in stock returns due to variations in foreign exchange rates had spilled over from one country to another within BRICS bloc (Sui and Sun, 2017).

A few studies had specifically analysed the impact of pandemics on different macro-economic variables, including stock market performances. It was observed that since 1900 many infectious diseases (e.g. Spanish Flu) had caused volatilities in macro-economic variables, including stock returns. However, studies reported that the impact of Covid-19 on stock markets all over the world had been unprecedented (Baker, et al., 2020). Sethi, Dash, Swain and Das (2021), in their study, used a sample of 37 nations and considered data from January 4, 2020, to April 30, 2021, to investigate how Covid-19 affected their currency exchange rate behaviour. The study used fixed-effect regression to show that the exchange rate responded favourably to the Covid-19 pandemic, especially to the number of confirmed cases and deaths per day.

Several studies that had specifically focused on the impact of Covid-19 on stock market returns had shown that stock markets of Japan, Korea, Singapore, the US, Germany, Italy and the United Kingdom (UK) had gone into recession immediately after the outbreak, and the situation was worst in Asian markets. Covid-19 led to pessimistic market sentiments, which were found to have adversely affected the post-listing abnormal returns. The study suggested that had policymakers and regulators apprehended the financial contagion effect of Covid-19 and taken appropriate steps to prevent its impact on the economy, such a catastrophe could be avoided (Liu, et al., 2020). One of the studies also showed that Covid-19 impacted six Latin American and the US stock markets in a non-linear way. However, it was observed that the Argentinean market managed to remain out of its clutch. According to the authors, insignificant contagion effect among these markets allowed the international investors there to carry out efficient portfolio diversification strategies and allowed the policy makers to carry out institutional reforms in ensuring market efficiency (Helidoro, et al., 2020). Khilar, Singh, Dash and Sethi (2022) in their study, used a sample of 34 nations from both emerging and developed economies to investigate how the stock markets of those nations responded to verified cases, deaths, and government-imposed lockdowns caused by Covid-19 based on a data from January 4, 2020, to September 30, 2020. The findings showed that the Covid-19 outbreak, specifically the daily confirmed cases and lockdown in both emerging and developed nations, had a detrimental impact on their stock markets.

Bhardwaj, Sharma, and Mavi (2022) revealed the potential effects of Covid-19 on the short- and long-term relationships among five growing Asian economies in a relatively recent study. In addition to South Korea, Indonesia, Taiwan, China, and India were included in their analysis, even though they did not specifically select the BRICS as their sample. According to the report, Covid-19 made it harder for the chosen economies to integrate. In actuality, those five nations' stock markets were not eventually integrated. Only the stock markets of South Korea and China reported short-term links following the outbreak, but the stock markets of those five countries had both unidirectional and bidirectional causal associations prior to the Covid-19 pandemic. On the other hand, Mishra and Mishra (2022) examined the impact of Covid-19 on the degree of integration among the BRICS stock markets. Their analysis indicates that during the epidemic, the markets were not interconnected. Such findings were actually influenced by vulnerable real interest rates, inflation rates, real currency rates, and a reduction in trade links between the countries.

While the BRICS countries' stock markets' lack of long-term integration allowed foreign investors to diversify their portfolios, it was also crucial to manage macroeconomic variables like inflation, interest rates, and exchange rates during the global crisis in order to promote steady economic growth and, ultimately, guarantee economic interconnectedness. There are relatively few studies that include BRICS, even though much of the research that was particularly examined in the paper examined the economic interconnectivity of the member countries of various economic blocs. Additionally, the authors have not found any noteworthy Indian research on the short-term causal relationships and long-term integration of the stock markets of the BRICS countries, particularly in times of global financial crises. Additionally, the literature reviewed thus far has not examined the effects of short-term causal links and long-term integration on the economic interconnection among the member countries. Given these gaps in the literature, the current work aims to fill them.

Based on the gaps in existing research reviewed so far and with a view to addressing the research questions, the study has been undertaken with the following major objectives:

(i) To estimate the long-run relationship among stock markets of BRICS nations in pre-; during and post-Covid-19 induced global crisis period.
(ii) To estimate causality among stock markets of BRICS nations in pre-; during and post-Covid-19 induced global crisis period.

## 3. Research Methodology

### 3.1. Sampling Design

With a view to analysing the long-run cointegration and causality among the stock markets of BRICS nations, their largest stock exchanges based on their market capitalisation have been identified (WEF, 2019). The stock index that best represents the market movements of each identified stock exchange is selected based on existing literature (Panda and Thiripalraju, 2021; Rout and Das, 2024). Selection of stock indices are shown below in Table 1:

**Table 1: Stock indices taken in the study**

| Country | Stock Exchange | Stock Index |
|---|---|---|
| Brazil | Brazil Stock Exchange and Over the Counter Market | IBOVESPA (BOVESPA) |
| Russia | Moscow Exchange | MOEX |
| India | Bombay Stock Exchange Ltd. (BSE) | Sensitivity Index (SENSEX) |
| China | Shanghai Stock Exchange (SSE) | SSE Composite Index (SSECI) |
| South Africa | Johannesburg Stock Exchange Ltd. (JSE) | JTOPI |

Source: Authors' compilation.

### 3.2. Data Collection

The period of study selected is October 24, 2019 to October 23, 2020. Data on the adjusted closing price of the aforesaid indices during the period is collected from www.investing.com. to remove the inconsistency in the dataset arising out of different operating days in different stock exchanges, appropriate data mining has been made. Ultimately, the study is made with 209 observations that conform to the same dates of operation of the select stock exchanges. The data for all the stock indices is then plotted (Figure 2). It is observed that stock markets in all the countries under consideration have passed through a recession, presumably due to the Covid-19 pandemic and its ensuing economic shutdown from February to June 2020, which falls between the full sample periods (October 24, 2019 to October 23, 2020). Based on this observation, the full-sample period has been segregated into three sub-sample periods: (a) pre-Covid-19 global crisis period (October 24, 2019 to February 23, 2020); (b) Covid-19 global crisis period (February 24, 2020 to June 23, 2020); and (c) post-Covid-19 global crisis period with transition (June 24, 2020 to October 23, 2020). The total of 209 observations of the full sample period have also been distributed almost equally among the pre-Covid-19 global crisis period (69 obs.), Covid-19 global crisis period (68 obs.) and the post-Covid-19 global crisis period (72 obs.). For further analysis, the data is then converted into their natural logarithmic form (LNBOVESPA; LNJTOPI, LNMOEX, LNSENSEX; and LNSSECI) to reduce skewness in the data.

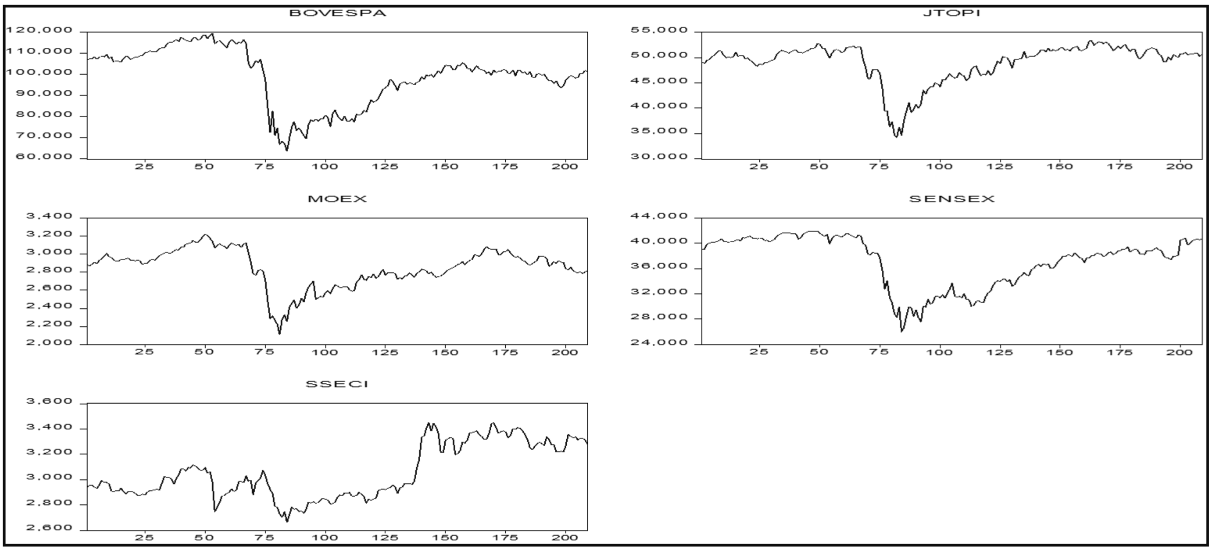


**Figure 2: Stock Market Performance of BRICS Countries**

## 3.3. Econometric Tools

Stationarity in the dataset is tested using the Augmented Dickey Fuller (ADF) test for each of the three sub-sample periods (McKinnon, 1991; Enders, 2004). In each sub-sample period, if the data series are integrated of the same order, long-run relationship among them is estimated using Johansen Julius (JJ) cointegration technique (Johansen, 1988). If the data series are cointegrated in the long run, long-run or short-run causality among them may be identified based on the underlying Vector Error Correction Model (VECM) (Thierry et al. 2016). However, if they are not cointegrated in the long run, their short-run causality may be estimated using the Vector Auto-regression (VAR) model (Toda and Phillips, 1991). If the data series are integrated of different orders, long-run relationships among them will be measured with the help of Bounds Test under the Auto-regressive Distributed Lag (ARDL) model (Pesaran et al., 2001). In this situation, short-run causality among the data series may be estimated using the Pair-wise Granger causality test (Rahman and Kashem, 2017; Granger, 1969).

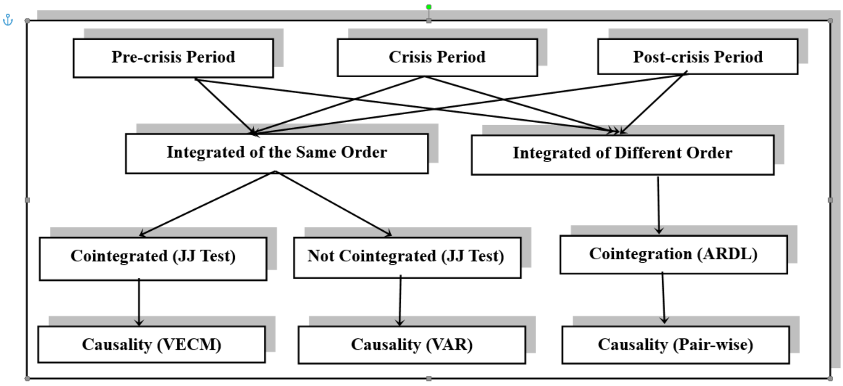


**Figure 3: Research Design**

# 4. Results and Discussion

## 4.1. Data Stationarity

DF test is based on following hypothesis: H0: $\delta = 0$ against H1:$\delta \neq 0$ where ρ is the autocorrelation between Yt and Yt-1 in the equation: $\Delta Y_t = \delta Y_{t-1} + u_t$. The test statistic under DF test is $\frac{\hat{\delta}}{SE(\hat{\delta})}$ which is compared with its critical value to make a decision about $H_0$. In case of ADF test, the DF regressions are augmented by including 'm' lags of the Dependent Variable (DV) to correct serial correlation in the disturbance term ($u_t$). Where m= Int. 12*(T/100)$^{1/4}$. In the present study ADF test is to be conducted to test whether the data series are random walk (RW) with drift ($\Delta Y_t = \alpha + \delta Y_t + \sum_{i=1}^{m} Y_i \Delta Y_{t-1} + \mu_t$) and RW with trend and drift ($\Delta Y_t = \alpha + \beta t + \delta Y_t + \sum_{i=1}^{m} Y_i \Delta Y_{t-1} + \mu_t$). Appropriate lag length is selected based on Schwarz Bayesian Criterion (SBC). If $H_0$ in both these models are accepted, the series is a non-stationary series and vice versa. If a log-transformed series is stationary at level, it is integrated of order 0 [I(0)], and if a series is non-stationary at level and stationary at first difference, it is integrated of order 1 [I(1)].

Results of ADF tests during three intermittent sub-sample periods exhibit that during pre-Covid-19 global crisis period (Panel A, Table 3), at 1% level of significance, all the data series are non-stationary at level (Prob.>0.01) and stationary at first difference (Prob.<0.01). During Covid-19 global crisis period (Panel B, Table 3), all the data series are non-stationary at level and stationary at first difference. Hence, all the data series during these two periods are I(1) series. However, during post-Covid-19 global crisis period with transition, all the data series are I(1) barring LNSSECI (Panel C, Table 3). It is an I(0) series.

## 4.2. Long-Run Relationship and Causality During Pre-Covid-19 Global Crisis Period

### 4.2.1. Long-Run Relationship

Since all the stock indices during pre-Covid-19 global crisis period are I(1), long run relationship among them is estimated using JJ Cointegration technique. There are two tests under this technique – (a) Trace test and (b) Max-Eigen value test. Trace test is conducted based on following hypothesis $H_0$: $r = r_1 < k$ [where r is number of distinct cointegrating vector(s)], against $H_1$: r=k. The test statistic for trace can be specified as $\lambda_{Trace} = -T \sum_{i=r+1}^{n} Ln(\lambda - 1)$. Where $\lambda_i$ is the i$^{th}$ largest value of cointegrating matrix Π and T is the number of observations. Here, Π = -(I – A1 – A2 - ...Ap) where I is an identity matrix and A1, A2,…Ap are coefficients in the equation $Zt = A1\,Zt - 1 + A2Zt - 2 + \ldots.Ap\,Zt - p + ut$ where $Zt = \{\text{LNBOVESPAt}, \text{LNJTOPIt}, \text{LNMOEXt}, \text{LNSENSEXt}, \text{LNSSECIt}\}$. On the other hand Max-Eigen value test is based on following hypothesis: $H_0$: $r = r_1 < k$ against $H_1$: $r = r_1 + 1$. The test statistics under Max-Eigen value test can be specified as $\lambda_{Max}$ = -T ln(1-$\lambda_{r+1}$) [where $\lambda_{Max}$ is the (r+1)$^{th}$ largest squared Eigen value]. The appropriate lag length is determined based on Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQC). The lag that reports the minimum value in AIC and SBC, is selected as the appropriate one. However, if there is an inconsistency in the lag length as per AIC and SBC, appropriate lag is selected based on HQC. The particular assumption for running the model is intercept but no trend in Cointegrating Equations (CE) and Vector Auto-Regression (VAR). The number of cointegrating relationship among the variables depends on number of hypothesised CEs for which the results of Trace and max-Eigen values are significant (Prob.<0.05 and $H_0$ cannot be accepted).

**Table 2: Results of JJ Cointegration Test (Pre-Covid-19 Global Crisis Period)**

| No. of Hypothesised CE(s) | Eigen Value | Trace Test | | | Max Eigen Value Test | | |
|---|---|---|---|---|---|---|---|
| | | Statistic | Prob. | Decision on $H_0$ | Statistic | Prob. | Decision on $H_0$ |
| **None** | 0.365 | 68.125 | 0.067 | Accepted | 29.473 | 0.153 | Accepted |
| **At most 1** | 0.232 | 38.651 | 0.274 | Accepted | 17.118 | 0.569 | Accepted |
| **At most 2** | 0.176 | 21.533 | 0.325 | Accepted | 12.611 | 0.488 | Accepted |
| **At most 3** | 0.072456 | 8.922124 | 0.3726 | Accepted | 4.888998 | 0.7558 | Accepted |
| **At most 4** | 0.060162 | 4.033126 | 0.0446* | Rejected | 4.033126 | 0.0446* | **Rejected** |

Note: *Significant at 5% level of significance.

Source: Authors' compilation.

At lag-length 1 (based on AIC, SBC, and HQC), the results of Trace test and Max-Eigen value test suggest that both trace statistic and max Eigen-value statistic are significant with at most 4 hypothesis CEs (Table 2). From the result, it may be concluded that at 5% level, there is no cointegration among the stock indices. Hence, there are no long-run relationships among stock indices in the pre-Covid-19 global crisis period.

**Table 3: Results of ADF tests for three intermittent sub-sample periods**

| Index | Level Prob. (Intercept) | Level Prob. (Trend and Intercept) | Result | First Difference Prob. (Intercept) | First Difference Prob. (Trend and Intercept) | Result | Data Series Nature at Level |
|---|---|---|---|---|---|---|---|
| **Panel A: Pre-Covid-19 Global Crisis Period (Maximum Lag as per SIC = 10)** | | | | | | | |
| **LNBOVESPA** | 0.499 | 0.563 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNJTOPI** | 0.391 | 0.452 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNMOEX** | 0.634 | 0.721 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSENSEX** | 0.016** | 0.039** | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSSECI** | 0.317 | 0.597 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **Panel B: Covid-19 Global Crisis Period (Maximum Lag as per SIC = 10)** | | | | | | | |
| **LNBOVESPA** | 0.429 | 0.397 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNJTOPI** | 0.683 | 0.229 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNMOEX** | 0.224 | 0.079* | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSENSEX** | 0.171 | 0.471 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSSECI** | 0.343 | 0.505 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **Panel C: Post-Covid-19 Global Crisis with Transition Period (Maximum Lag as per SIC = 11)** | | | | | | | |
| **LNBOVESPA** | 0.090* | 0.159 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNJTOPI** | 0.092* | 0.125 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNMOEX** | 0.514 | 0.905 | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSENSEX** | 0.248 | 0.098* | Non-Stationary | 0.001*** | 0.001*** | Stationary | I(1) |
| **LNSSECI** | 0.001*** | 0.001*** | Stationary | NA | NA | | I(0) |

Note: *, ** and *** show significance at 10%, 5% and 1% respectively.
Source: Authors compilation.

### 4.2.2. Short-Run Causality

Since stock indices are not cointegrated, the short-run causal relationship among them may be estimated using underlying VAR model after converting the data into first differences as follows:

$\Rightarrow$ $\Delta LNBOVESPA_t = a_0 + \sum_{j=1}^{p} a_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} a_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} a_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} a_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} a_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$….(1)

$\Rightarrow$ $\Delta LNJTOPI_t = b_0 + \sum_{j=1}^{p} b_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1p}^{p} b_2\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} b_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} b_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} b_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$….(2)

$\Rightarrow$ $\Delta LNMOEX_t = c_0 + \sum_{j=1}^{p} c_{1p}\,\Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} c_{2p}\,\Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} c_{3p}\,\Delta LNMOEX_{t-j} + \sum_{j=1}^{p} c_{4p}\,\Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} c_{5p}\,\Delta LNSSECI_{t-j} + \mu_t$….(3)

$\Rightarrow$ $\Delta LNSENSEX_t = d_0 + \sum_{j=1}^{p} d_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} d_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} d_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} d_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} d_{5}\, \Delta LNSSECI_{t-j} + \mu_t$....(4)

$\Rightarrow$ $\Delta LNSSECI_t = e_0 + \sum_{j=1}^{p} e_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} e_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} e_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} e_{p4}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} e_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(5)

The short-run causality among the stock indices is estimated using Granger causality in VAR (Block Exogeneity Wald test) with the following hypothesis. $H_0$: $R_\alpha=0$; against $H_1$: $R_\alpha \neq 0$ (where α is the vector of all VAR coefficients and R is suitably chosen non-causality restriction matrix having full row rank. The Wald statistic is $T\hat{\alpha}R'(R\widehat{\sum_{\hat{\alpha}} R'})^{-1}$where T=sample size; $\hat{\alpha}$ is the asymptotically normally distributed estimator of α; $\sum_{\hat{\alpha}} R$ is the covariance matrix of the asymptotic distribution and $\widehat{\sum_{\hat{\alpha}} R'}$is its estimator. It follows $\chi^2$(p-1) distribution. At 5% level of significance, if test statistics>critical value, $H_0$ cannot be accepted and vice versa. If $H_0$ cannot be accepted, causal relationship exists among two variables. For each equation in the model, causal effects of exogenous indices on endogenous index is measured individually and together.

**Table 4: Results of VAR Granger Causality Test (Pre-Covid-19 Global Crisis Period)**

| DV | IV | $\chi^2$ | Prob. | Decision Rule | Decision on $H_0$ | Results |
|---|---|---|---|---|---|---|
| **DLNBOVESPA** | **DLNJTOPI** | 1.50 | 0.22 | Prob.>0.05 | Accepted | DLNJTOPI ↛ DLNBOVESPA |
| | **DLNMOEX** | 0.05 | 0.81 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNBOVESPA |
| | **DLNSENSEX** | 0.83 | 0.36 | Prob.>0.05 | Accepted | DLNSENSEX ↛ DLNBOVESPA |
| | **DLNSSECI** | 0.95 | 0.33 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNBOVESPA |
| | **All** | 3.96 | 0.41 | Prob.>0.05 | Accepted | All↛ DLNBOVESPA |
| **DLNJTOPI** | **DLNBOVESPA** | 0.76 | 0.38 | Prob.>0.05 | Accepted | DLNBOVESPA↛ DLNJTOPI |
| | **DLNMOEX** | 0.26 | 0.61 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNJTOPI |
| | **DLNSENSEX** | 0.02 | 0.88 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNJTOPI |
| | **DLNSSECI** | 1.64 | 0.20 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNJTOPI |
| | **All** | 3.18 | 0.52 | Prob.>0.05 | Accepted | All↛ DLNJTOPI |
| **DLNMOEX** | **DLNBOVESPA** | 2.75 | 0.09 | Prob.>0.05 | Accepted | DLNBOVESP↛DL NMOEX |
| | **DLNJTOPI** | 5.08 | 0.02 | Prob.<0.05 | Rejected | **DLNJTOPI→DLN MOEX** |
| | **DLNSENSEX** | 1.47 | 0.22 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNMOEX |
| | **DLNSSECI** | 0.06 | 0.81 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNMOEX |
| | **All** | 11.64 | 0.02 | Prob.>0.05 | Accepted | All↛ DLNMOEX |
| **DLNSENSEX** | **DLNBOVESPA** | 3.39 | 0.06 | Prob.>0.05 | Accepted | DLNBOVESPA↛ DLNSENSEX |
| | **DLNJTOPI** | 6.05 | 0.01 | Prob.<0.05 | Rejected | **DLNJTOPI→ DLNSENSEX** |
| | **DLNMOEX** | 0.00 | 0.99 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNSENSEX |
| | **DLNSSECI** | 0.46 | 0.49 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNSENSEX |
| | **All** | 11.91 | 0.02 | Prob.<0.05 | Rejected | **All→ DLNSENSEX** |

| DV | IV | $\chi^2$ | Prob. | Decision Rule | Decision on $H_0$ | Results |
|---|---|---|---|---|---|---|
| DLNSSECI | **DLNBOVESPA** | 6.35 | 0.01 | Prob.<0.05 | Rejected | **DLNBOVESPA→ DLNSSECI** |
| | **DLNJTOPI** | 3.59 | 0.05 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNSSECI |
| | **DLNMOEX** | 5.61 | 0.01 | Prob.<0.05 | Rejected | **DLNMOEX→ DLNSSECI** |
| | **DLNSENSEX** | 1.91 | 0.16 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNSSECI |
| | **All** | 19.78 | 0.00 | Prob.<0.05 | Rejected | **All→ DLNSSECI** |

Source: Authors' compilation.

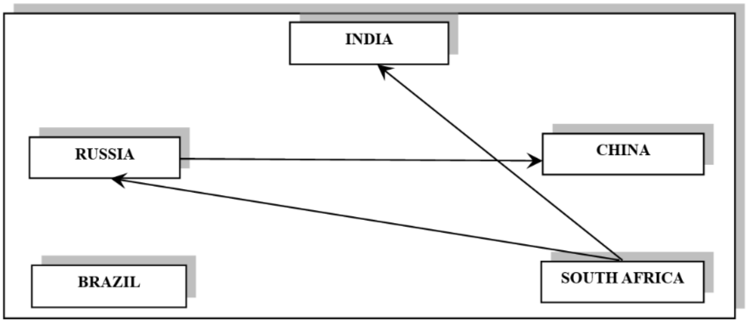


**Figure 4: Causality Diagram (Pre-Crisis Period)**

The results of the test (Table 4) suggest that stock markets return (first difference of stock indices data) of South African market (DLNJTOPI) Granger cause returns in Russian (DLNMOEX) and Indian market (DLNSENSEX). On the other hand, returns in Chinese stock market (DLNSSECI) is Granger caused by returns of Brazilian (DLNBOVESPA) and Russian market. Stock market returns in India is Granger caused by the remaining four countries in the model. Stock returns of Chinese market is also Granger caused by other four countries.

## 4.3. Long-Run Relationship and Causality During Covid-19 Global Crisis Period

### 4.3.1. Long-Run Relationship

All stock indices during the Covid-19 global crisis are I(1) series (Table 3). With a view to exploring the long-run relationship among the stock indices during this period, JJ Cointegration technique is applied. At lag-length 1 (as per HQC) and with the assumption of linear deterministic trend, the results of Trace test indicate 2 cointegrating relationship at 5% level of significance (at no and at most 1 hypothesised CE) (Table 5).

**Table 5: Results of Johansen Cointegration Test (Covid-19 Global Crisis Period)**

| No. of Hypothesised CE(s) | Eigen Value | Trace Test | | | Max Eigen Value Test | | |
|---|---|---|---|---|---|---|---|
| | | Statistic | Prob. | Decision on $H_0$ | Statistic | Prob. | Decision on $H_0$ |
| None | 0.406 | 86.917 | 0.001* | Rejected | 34.367 | 0.044* | Rejected |
| At most 1 | 0.325 | 52.550 | 0.017* | Rejected | 25.997 | 0.079 | Accepted |
| At most 2 | 0.174 | 26.553 | 0.113 | Accepted | 12.679 | 0.482 | Accepted |
| At most 3 | 0.144 | 13.874 | 0.086 | Accepted | 10.292 | 0.194 | Accepted |
| At most 4 | 0.052 | 3.582 | 0.058 | Accepted | 3.582 | 0.058 | Accepted |

Note: *Significant at 5% level of significance.
Source: Authors' compilation.

However, Max Eigen-value test indicates only 1 cointegrating relationship at 5% level of significance (at no hypothesised CE). It may be concluded that stock indices are cointegrated during this period. Hence, there exists a long-run relationship among the stock market performances of the BRICS nations during Covid-19 global crisis period.

### 4.3.2. Long-Run Causality

Since the stock indices are cointegrated, long-run causality among them may be estimated based on the underlying Vector Error Correction Model (VECM), in which the error term from the cointegration equation lagged once is the Error Correction Term (ECT) as follows:

⇒ $\Delta LNBOVESPA_t = a_0 + \lambda_1 \epsilon_{t-1} + \sum_{j=1}^{p} a_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} a_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} a_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} a_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} a_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(6)

⇒ $\Delta LNJTOPI_t = b_0 + \lambda_2 \epsilon_{t-1} + \sum_{j=1}^{p} b_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1p}^{p} b_2\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} b_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} b_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} b_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(7)

⇒ $\Delta LNMOEX_t = c_0 + \lambda_3 \epsilon_{t-1} + \sum_{j=1}^{p} c_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} c_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} c_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} c_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} c_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(8)

⇒ $\Delta LNSENSEX_t = d_0 + \lambda_4 \epsilon_{t-1} + \sum_{j=1}^{p} d_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} d_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} d_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} d_{4p}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} d_5\, \Delta LNSSECI_{t-j} + \mu_t$....(9)

⇒ $\Delta LNSSECI_t = e_0 + \lambda_5 \epsilon_{t-1} + \sum_{j=1}^{p} e_{1p}\, \Delta LNBOVESPA_{t-j} + \sum_{j=1}^{p} e_{2p}\, \Delta LNJTOPI_{t-j} + \sum_{j=1}^{p} e_{3p}\, \Delta LNMOEX_{t-j} + \sum_{j=1}^{p} e_{p4}\, \Delta LNSENSEX_{t-j} + \sum_{j=1}^{p} e_{5p}\, \Delta LNSSECI_{t-j} + \mu_t$....(10)

Here, $\epsilon_{t-1}$ is the ECT which can be written as $LNBOVESPA_{t-1} + \beta_0 + \beta_1 LNJTOPI_{t-1} + \beta_2 LNMOEX_{t-1} + \beta_3 LNSENSEX_{t-1} + \beta_4 LNSSECI_{t-1}$; and $\lambda_i$ is the ECT coefficient, which measures the speed of an exogenous shock. This can be adjusted back to the equilibrium. If $\lambda_i<0$ and significant at 5% level of significance, the endogenous variable and other regressor variables have long-run causality flowing from the latter to the former. Here, the cointegrating relationship among the stock indices during Covid-19 global crisis period may be represented as follows:

⇒ LNBOVESPA(-1)=-0.856262125271*LNJTOPI(-1)+0.991349525471*LNMOEX(-1)+ 0.951804268637*LNSENSEX(-1) + 3.13235263005*LNSSECI(-1) - 22.1136791016 ......... (11)

⇒ ECT=LNBOVESPA(-1)+0.856262125271*LNJTOPI(-1)-0.991349525471*LNMOEX(-1)- 0.951804268637*LNSENSEX(-1)-3.13235263005*LNSSECI(-1)+22.1136791016........ (12)

VECM estimates give equations considering five stock indices individually as endogenous variables:

⇒ D(LNBOVESPA)=C(1)*ECT+C(2)*D(LNBOVESPA(-1))+ C(3)*D(LNJTOPI(-1)) + C(4)*D(LNMOEX(-1)) + C(5)*D(LNSENSEX(-1)) + C(6)*D(LNSSECI(-1)) + C(7)...............(13)

⇒ D(LNJTOPI)= C(8)*ECT+ C(9)*D(LNBOVESPA(-1)) + C(10)*D(LNJTOPI(-1)) + C(11)*D(LNMOEX(-1)) + C(12)*D(LNSENSEX(-1)) + C(13)*D(LNSSECI(-1)) + C(14)................(14)

⇒ D(LNMOEX)=C(15)*ECT+C(16)*D(LNBOVESPA(-1))+C(17)*D(LNJTOPI(-1)) + C(18)*D(LNMOEX(-1)) + C(19)*D(LNSENSEX(-1)) + C(20)*D(LNSSECI(-1)) + C(21)................(15)

⇒ D(LNSENSEX)=C(22)*ECT+C(23)*D(LNBOVESPA(-1))+C(24)*D(LNJTOPI(-1))+ C(25)*D(LNMOEX(-1)) + C(26)*D(LNSENSEX(-1)) + C(27)*D(LNSSECI(-1)) + C(28)................(16)

⇒ D(LNSSECI)=C(29)*ECT+C(30)*D(LNBOVESPA(-1))+C(31)*D(LNJTOPI(-1)) + C(32)*D(LNMOEX(-1)) + C(33)*D(LNSENSEX(-1)) + C(34)*D(LNSSECI(-1)) + C(35)...............(17)

In Eqn. (13) to (17), coefficients of ECTs [C(1); C(8); C(15); C(22); and C(29)] measure the speed of adjustment of any deviation from the long-run equilibrium back to the equilibrium through partial short-run dynamic adjustments. In order to test the $H_0$ of no long-run causality of one stock index with the remaining four indices, the significance of the coefficients at 5% level is estimated using OLS procedure. If the coefficient is negative and significant (Prob.<0.05), the endogenous stock index is caused by the other four indices in the long-run. The estimated values of the coefficient, t-statistic and probability values are shown in the following table.

**Table 6: Statistical Significance of ECT Coefficients**

| Equation | Coefficient | Estimate | Decision | t-statistic | Prob. | Decision Rule | Decision |
|---|---|---|---|---|---|---|---|
| **13** | **C(1)** | -0.305 | Estimate<0 | 3.213 | 0.001 | Prob.<0.05 | Rejected |
| **14** | **C(8)** | -0.211 | Estimate<0 | 4.095 | 0.001 | Prob.<0.05 | Rejected |
| **15** | **C(15)** | -0.248 | Estimate<0 | 5.529 | 0.000 | Prob.<0.05 | Rejected |
| **16** | **C(22)** | -0.221 | Estimate<0 | 3.609 | 0.001 | Prob.<0.05 | Rejected |
| **17** | **C(29)** | -0.082 | Estimate<0 | 3.547 | 0.001 | Prob.<0.05 | Rejected |

Source: Authors' compilation.

The coefficients of the ECTs are all significant at 5% level of significance, and they are all negative. Hence, each stock index during the Covid-19 global crisis is caused by the remaining 4 stock indices in the long-run.

### 4.3.3. Short-Run Causality

Short-run causality among the stock indices is estimated using Block Exogeneity Wald test on level data. However, here the underlying model is VECM.

**Table 7: Results of VEC Granger Causality Test (Covid-19 Global Crisis Period)**

| Dependent Variable | Independent Variables | Chi-Square | Prob. | Decision Rule | Decision on $H_0$ | Results |
|---|---|---|---|---|---|---|
| **DLNBOVESPA** | **DLNJTOPI** | 1.469 | 0.22 | Prob.>0.05 | Accepted | DLNJTOPI ↛ DLNBOVESPA |
| | **DLNMOEX** | 2.428 | 0.12 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNBOVESPA |
| | **DLNSENSEX** | 0.921 | 0.34 | Prob.>0.05 | Accepted | DLNSENSEX ↛ DLNBOVESPA |
| | **DLNSSECI** | 4.889 | 0.03 | Prob.<0.05 | Rejected | **DLNSSECI→ DLNBOVESPA** |
| | **All** | 7.991 | 0.09 | Prob.>0.05 | Accepted | All↛ DLNBOVESPA |
| **DLNJTOPI** | **DLNBOVESPA** | 0.594 | 0.44 | Prob.>0.05 | Accepted | DLNBOVESPA ↛ DLNJTOPI |
| | **DLNMOEX** | 15.661 | 0.00 | Prob.<0.05 | Rejected | **DLNMOEX→ DLNJTOPI** |
| | **DLNSENSEX** | 10.934 | 0.00 | Prob.<0.05 | Rejected | **DLNSENSEX→ DLNJTOPI** |
| | **DLNSSECI** | 10.574 | 0.00 | Prob.<0.05 | Rejected | **DLNSSECI→ DLNJTOPI** |
| | **All** | 34.891 | 0.00 | Prob.<0.05 | Rejected | **All→ DLNJTOPI** |
| **DLNMOEX** | **DLNBOVESPA** | 0.181 | 0.67 | Prob.>0.05 | Accepted | DLNBOVESP↛ DLNMOEX |
| | **DLNJTOPI** | 9.608 | 0.00 | Prob.<0.05 | Rejected | **DLNJTOPI→D LNMOEX** |
| | **DLNSENSEX** | 6.672 | 0.00 | Prob.<0.05 | Rejected | **DLNSENSEX→ DLNMOEX** |
| | **DLNSSECI** | 12.548 | 0.00 | Prob.<0.05 | Rejected | **DLNSSECI→ DLNMOEX** |
| | **All** | 26.828 | 0.00 | Prob.<0.05 | Rejected | **All→** |

| Dependent Variable | Independent Variables | Chi-Square | Prob. | Decision Rule | Decision on $H_0$ | Results |
|---|---|---|---|---|---|---|
| | | | | | | **DLNMOEX** |
| **DLNSENSEX** | **DLNBOVESPA** | 0.804 | 0.36 | Prob.>0.05 | Accepted | DLNBOVESPA ↛ DLNSENSEX |
| | **DLNJTOPI** | 4.614 | 0.03 | Prob.<0.05 | Rejected | **DLNJTOPI→ DLNSENSEX** |
| | **DLNMOEX** | 6.791 | 0.01 | Prob.<0.05 | Rejected | **DLNMOEX→ DLNSENSEX** |
| | **DLNSSECI** | 8.878 | 0.00 | Prob.<0.05 | Rejected | **DLNSSECI→ DLNSENSEX** |
| | **All** | 18.961 | 0.00 | Prob.<0.05 | Rejected | **All→ DLNSENSEX** |
| **DLNSSECI** | **DLNBOVESPA** | 0.001 | 0.98 | Prob.>0.05 | Accepted | DLNBOVESPA ↛ DLNSSECI |
| | **DLNJTOPI** | 0.304 | 0.58 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNSSECI |
| | **DLNMOEX** | 3.425 | 0.06 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNSSECI |
| | **DLNSENSEX** | 5.048 | 0.02 | Prob.<0.05 | Rejected | **DLNSENSEX→ DLNSSECI** |
| | **All** | 9.286 | 0.05 | Prob.>0.05 | Accepted | All↛ DLNSSECI |

Source: Authors' compilation.

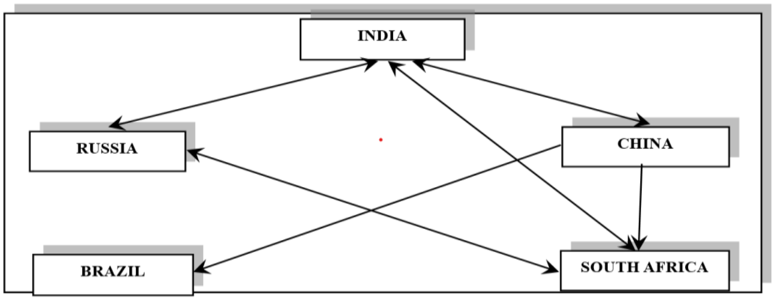


**Figure 5: Causality Diagram (Crisis Period)**

The results suggest that there exists a bidirectional causality between the stock indices of Russia and South Africa; India and South Africa; India and Russia; and India and China, and unidirectional causality between the stock indices of China and Brazil; China and South Africa; and China and Russia flowing from China to the other countries. Stock markets in South Africa, Russia and India separately are Granger caused by the remaining four countries.

## 4.4. Long-Run Relationship and Causality During Post-Covid-19 Global Crisis Period

### 4.4.1. Long-Run Relationship

During the post-Covid-19 global crisis period, LNBOVESPA, LNMOEX, LNJTOPI and LNSENSEX are I(1) series, while LNSSECI is an I(0) series. Since the stock market indices are integrated of different orders, long run relationships among the stock indices may be estimated with level data using ARDL technique, which is less restrictive to the order of integration:

$$\Rightarrow \Delta LNBOVESPA_t = a_0 + \sum_{i=1}^{n} a_{1i}\,\Delta LNBOVESPA_{t-i} + \sum_{i=0}^{n} a_{2i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} a_{3i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} a_{4i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} a_{5i}\,\Delta LNSSECI_{t-i} + a_6 LNBOVESPA_{t-1} + a_7 LNJTOPI_{t-1} + a_8 LNMOEX_{t-1} + a_9 LNSENSEX_{t-1} + a_{10} LNSSECI_{t-1} + \mu_t \,..\, (1)$$

$\Rightarrow$ $\Delta LNJTOPI_t = b_0 + \sum_{i=1}^{n} b_{1i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} b_{2i}\,\Delta LNBOVESPA_{t-i} + \sum_{i=0}^{n} b_{3i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} b_{4i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} b_{5i}\,\Delta LNSSECI_{t-i} + b_6 LNBOVESPA_{t-1} + b_7 LNJTOPI_{t-1} + b_8 LNMOEX_{t-1} + b_9 LNSENSEX_{t-1} + b_{10} LNSSECI_{t-1} + \mu_t$...(2)

$\Rightarrow$ $\Delta LNMOEX_t = c_0 + \sum_{i=1}^{n} c_{1i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} c_{2i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} c_{3i}\,\Delta LNBOVESPA_{t-i} + \sum_{i=0}^{n} c_{4i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} c_{5i}\,\Delta LNSSECI_{t-i} + c_6 LNBOVESPA_{t-1} + c_7 LNJTOPI_{t-1} + c_8 LNMOEX_{t-1} + c_9 LNSENSEX_{t-1} + cLNSSECI_{t-1} + \mu_t$....(3)

$\Rightarrow$ $\Delta LNSENSEX_t = d_0 + \sum_{i=1}^{n} d_{1i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} d_{2i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} d_{3i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} d_{4i}\,\Delta LNBOVESPA_{t-i} + \sum_{i=0}^{n} d_{5i}\,\Delta LNSSECI_{t-i} + d_6 LNBOVESPA_{t-1} + d_7 LNJTOPI_{t-1} + d_8 LNMOEX_{t-1} + d_9 LNSENSEX_{t-1} + d_{10} LNSSECI_{t-1} + \mu_t$....(4)

$\Rightarrow$ $\Delta LNSSECI_t = e_0 + \sum_{i=1}^{n} e_{1i}\,\Delta LNSSECI_{t-i} + \sum_{i=0}^{n} e_{2i}\,\Delta LNJTOPI_{t-i} + \sum_{i=0}^{n} e_{3i}\,\Delta LNMOEX_{t-i} + \sum_{i=0}^{n} e_{4i}\,\Delta LNSENSEX_{t-i} + \sum_{i=0}^{n} e_{5i}\,\Delta LNBOVESPA_{t-i} + e_6 LNBOVESPA_{t-1} + e_7 LNJTOPI_{t-1} + e_8 LNMOEX_{t-1} + e_9 LNSENSEX_{t-1} + e_{10} LNSSECI_{t-1} + \mu_t$..(5)

The Bounds test under ARDL technique is based on the following hypothesis, considering LNSENSEX as the DV and others as dynamic regressors. $H_0$: $d_6=d_7....=d_{10}=0$; against $H_1$: $d_6 \neq d_7.... \neq d_{10} \neq 0$. The asymptotic distribution of the F-statistic is non-standard. There are sets of critical values at a given significance level. While one set assumes that the variables are I(0), the other assumes that they are I(1). If the computed F-statistic exceeds the upper bound critical value [I(1)], $H_0$ of no cointegration cannot be accepted. However, if the computed F-statistic is less than the lower bound critical value [I(0)], $H_0$ of no cointegration is accepted. If F-statistic falls between these two bounds, the result is inconclusive. The appropriate lag length as per AIC, SBC, and HQC criteria is as follows: 1. The results of ARDL Bound test with LNSENSEX as the DV and other stock indices as dynamic regressors with lag 1 is shown in Table 8.

**Table 8: Results of ARDL Bounds Test**

| F Statistics | Significance Level | I(0) Bound | I(1) Bound | Decision Rule | Decision on $H_0$ |
|---|---|---|---|---|---|
| 1.538147 | 10% | 2.2 | 3.09 | F-Stat<I(0) Bound | Accepted |
| 1.538147 | 5% | 2.56 | 3.49 | F-Stat<I(0) Bound | Accepted |
| 1.538147 | 2.5% | 2.88 | 3.87 | F-Stat<I(0) Bound | Accepted |
| 1.538147 | 1% | 3.29 | 4.37 | F-Stat<I(0) Bound | Accepted |

Source: Authors' compilation.

Since the value of F-statistics is lower than the critical value of I(0) bound at difference levels of significance, there is no long-run relationship among the stock market indices during post-Covid-19 global crisis period.

### 4.4.2. Short-Run Causality

Since stock indices during this period are integrated of different orders, short-run causality among them may be estimated using Pair-wise Granger causality (F) test considering all the data at their first difference. In Eqn. (1) to (5), Granger causality between BOVESPA and JTOPI can be tested based on the following hypothesis: $H_0$: $b_{11} = b_{12} = ...\ b_{1p} = 0$ against $H_1$: $b_{11} \neq b_{12} \neq ... \neq b_{1p} \neq 0$ (it may be applied in all the other pairs). The test statistic (F) = $(RSS_R - RSS_{UR})*(n-k)/RSS_{UR}*m$ Where, $RSS_R$ is the Residual Sum of Square (RSS) of the regression where one variable is regressed against the lagged value of same variable; $RSS_{UR}$ is the RSS of the regression of the same variable regressed against the lagged value of same variable and other variables. At (n-k) df and 5% level of significance, if Prob.<0.05, $H_0$ of non-causality cannot be accepted and vice versa. If both the variables Granger cause one another, it is called bi-directional causality. If any one of the variables Granger causes the other, it is called unidirectional causality.

**Table 9: Results of Pair-wise Granger Causality Test**

| Null Hypothesis ($H_0$) | F-Statistic | Prob. | Decision Rule | Decision on $H_0$ | Results |
|---|---|---|---|---|---|
| **DLNJTOPI does not Granger Cause DLNBOVESPA** | 3.51154 | 0.0652 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNBOVESPA |
| **DLNBOVESPA does not Granger Cause DLNJTOPI** | 0.64420 | 0.4249 | Prob.>0.05 | Accepted | DLNBOVESPA↛ DLNJTOPI |
| **DLNMOEX does not Granger Cause DLNBOVESPA** | 0.21421 | 0.6449 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNBOVESPA |
| **DLNBOVESPA does not Granger Cause DLNMOEX** | 0.00698 | 0.9337 | Prob.>0.05 | Accepted | DLNBOVESPA↛ DLNMOEX |
| **DLNSENSEX does not Granger Cause DLNBOVESPA** | 4.62633 | 0.0350 | Prob.<0.05 | Rejected | **DLNSENSEX →DLNBOVESPA** |
| **DLNBOVESPA does not Granger Cause DLNSENSEX** | 6.50161 | 0.0130 | Prob.<0.05 | Rejected | **DLNBOVESPA →DLNSENSEX** |
| **DLNSSECI does not Granger Cause DLNBOVESPA** | 0.18397 | 0.6693 | Prob.>0.05 | Accepted | DLNSSECI ↛ DLNBOVESPA |
| **DLNBOVESPA does not Granger Cause DLNSSECI** | 0.57150 | 0.4522 | Prob.>0.05 | Accepted | DLNBOVESPA↛ DLNSSECI |
| **DLNMOEX does not Granger Cause DLNJTOPI** | 0.67447 | 0.4143 | Prob.>0.05 | Accepted | DLNMOEX ↛ DLNJTOPI |
| **DLNJTOPI does not Granger Cause DLNMOEX** | 0.10381 | 0.7483 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNMOEX |
| **DLNSENSEX does not Granger Cause DLNJTOPI** | 1.10415 | 0.2970 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNJTOPI |
| **DLNJTOPI does not Granger Cause DLNSENSEX** | 1.22918 | 0.2714 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNSENSEX |
| **DLNSSECI does not Granger Cause DLNJTOPI** | 3.42636 | 0.0684 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNJTOPI |
| **DLNJTOPI does not Granger Cause DLNSSECI** | 0.00044 | 0.9834 | Prob.>0.05 | Accepted | DLNJTOPI↛ DLNSSECI |
| **DLNSENSEX does not Granger Cause DLNMOEX** | 0.53529 | 0.4669 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNMOEX |
| **DLNMOEX does not Granger Cause DLNSENSEX** | 0.11231 | 0.7386 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNSENSEX |
| **DLNSSECI does not Granger Cause DLNMOEX** | 0.40959 | 0.5243 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNMOEX |
| **DLNMOEX does not Granger Cause DLNSSECI** | 0.07936 | 0.7790 | Prob.>0.05 | Accepted | DLNMOEX↛ DLNSSECI |
| **DLNSSECI does not Granger Cause DLNSENSEX** | 0.01474 | 0.9037 | Prob.>0.05 | Accepted | DLNSSECI↛ DLNSENSEX |
| **DLNSENSEX does not Granger Cause DLNSSECI** | 1.10904 | 0.2960 | Prob.>0.05 | Accepted | DLNSENSEX↛ DLNSSECI |

Source: Authors' compilation.

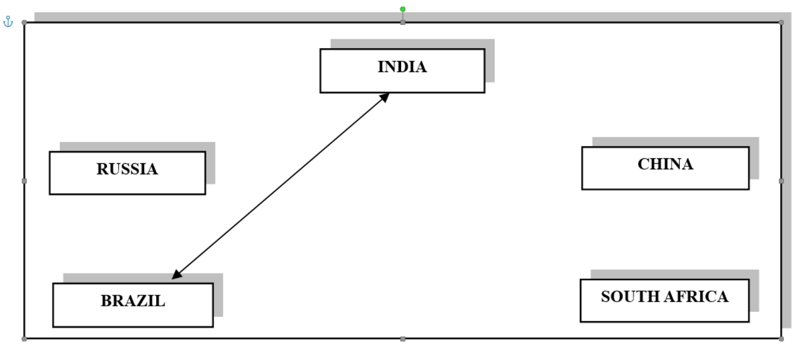


**Figure 6: Causality Diagram (Post-Crisis Period)**

At lag 1, results of Granger causality test suggest that bidirectional causality exists only between the stock marks returns of Brazil and India. However, there is no causal relationship among the stock market returns of any other countries during this period.

## 5. Conclusion

During the pre-crisis period, BRICS stock markets were not cointegrated. However, despite their Geo-political and economic diversity, stock markets of BRICS nations were integrated in the long-run by the sighting of the black swan due to Covid-19 and its ensuing economic shutdown, which continued in the post-Covid-19 transition phase as well. During February to June 2020, stock markets have gone into an acute recession and such adverse market sentiments in all the countries might have resulted in their cointegration. However, the studies Bhardwaj, Sharma, and Mavi (2022) and Mishra and Mishra (2022) showed that the BRICS stock markets were not integrated during the Covid-19 pandemic. The results in their studies differed, perhaps due to a different study period. However, Rout and Das (2024) had observed an increased association among the BRICS stocks during the crisis. Volatility spill-over effect had also been observed in G7 bloc due to the integration of their markets (Yosef, 2020). Just prior to the crisis, South African stock market Granger caused the Russian and Indian stock markets, while the Russian stock market Granger caused the Chinese stock market. However, during the crisis period, a robust causal relationship has been observed among all the stock markets, possibly due to their coordinated actions towards prevention and treatment of Covid-19 and providing a favourable condition for the supply of equipment. Specifically, bi-directional causality was observed between the stock markets of Russia and South Africa; India and South Africa; India and Russia; and India and China. Furthermore, during the crisis period, the Chinese stock market Granger caused Brazilian, South African and Russian stock markets. However, the moment Covid-19 entered a transition phase, all the aforesaid causal relationships ceased to exist. Only the stock markets of India and Brazil were connected through a bi-directional causal relationship.

Prior to the Covid-19 led economic crisis, the BRICS stock markets were not cointegrated. It allowed the Foreign Portfolio Investors (FPIs) to manage their portfolio risk by diversifying their investments among the BRICS stock markets. However, due to short term causal interactions among the stock markets of India, China, Russia and South Africa, the investors were required to adjust their diversification strategies. Since the Brazilian stock market was out of such causal interaction, FPIs could have focussed on this market to build a resilient portfolio. During the crisis, the stock markets of the BRICS bloc were interconnected over the long term. It did not allow the FPIs to diversify their investors in this bloc. Furthermore, the existence of causal relationships among all the countries also creates a possibility of volatility spill-over. Hence, creating a resilient portfolio based on the stocks of these markets was almost impossible. The situation continued in the transition phase as well. However, during this phase, only Indian and Brazilian stock markets were causing one another, allowing FPIs to form a resilient portfolio by focusing on the remaining three markets. Truly speaking, stock market integration and causality among two or more nations are the results of their economic cooperation stemming from multilateral trade agreements and other strategic ties. Policymakers of a particular country have a significant influence on such cooperation. Keeping in view the results, Indian policymakers may usually encourage India's economic ties with other member countries in the BRICS bloc and allow Indian investors to diversify their portfolio by investing in the other BRICS stock markets. But they should be cautious about any adversities in the South African market. However, whenever there is a crisis that can cause global economic turbulence, Indian policymakers should curb all economic ties with other member nations to avoid any spill-over effect and investors are advised to withdraw their investments from those markets during times of crisis. Liu, et al. (2020) and Helidoro, et al. (2020) also came up with the same conclusions in their respective studies. The status quo should be maintained even in the transition era.

The limitations of the study as identified by the authors, are as follows:

(a) Taking into account a limited time frame (October 2019 to October 2020) during which the stock markets of nearly all of the member countries experienced a severe decline as a result of global economic downturns, the current study attempted to determine the long-term integration and short-term causality among the stock markets of BRICS countries; however, taking into account a longer study period might have yielded a more trustworthy result.

(b) The study has considered five notable stock indices from the five member nations. While the authors have referred a few literature where these indices have been used to measure the stock market movements, the authors have used judgement sampling in initially selecting these indices, which is a limitation of the current study.

(c) The study has considered only BRICS bloc for drawing its conclusions. A similar analysis on other economic blocs (e.g. OECD, G7) and its comparison with the findings of this study may be considered in future research.

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# Corporate Social Responsibility As Moderator in CAPEX-Performance Relationship: Evidence from Indian Firms

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**Keywords**

Capital Expenditure, Corporate Social Responsibility, Firm Performance, Sustainability, Return on Assets, Tobin's Q

**JEL Classification**

G31, M14, L25

**Abstract:** This study investigates the impact of Capital Expenditure (CAPEX) on company performance and examines the moderating role of Corporate Social Responsibility (CSR) in this relationship. While organisations invest in CAPEX to achieve strategic goals and enhance shareholder value, integrating CSR into these decisions can align business growth with societal and sustainability objectives. Focusing on Indian companies listed on the NSE from 2016–17 to 2023–24, the study employs panel data regression analysis to evaluate the effects of CAPEX on performance indicators such as return on assets (ROA) and Tobin's Q. The findings reveal that CAPEX has a negative effect on both ROA and Tobin's Q; however, engagement in CSR initiatives can help offset these negative impacts. These results provide valuable insights for corporate managers, highlighting the importance of strategic CSR integration to improve investment decisions and resource allocation. The study contributes to existing literature by offering a novel perspective on the CAPEX-CSR-performance nexus and opens new directions for future research.

## 1. Introduction

Capital Expenditure (CAPEX) is generally perceived as a strategic tool for businesses to maintain and expand their operations. It plays a pivotal role in enhancing firm performance. While it requires significant financial commitment, the long-term benefits such as growth, efficiency, competitive advantage, and sustainability far outweigh the initial costs. Effective management of CAPEX ensures that firms remain agile, profitable, and well-positioned for future challenges. Research suggests that CAPEX leads to an enhanced market value of firms and operating efficiency, which in turn positively impacts firm performance (Abel & Eberly, 2011).

In India, CSR has progressed from philanthropic gestures to a further deliberate business function. It was mandated by the Companies Act 2013 for firms above thresholds to allocate a minimum of 2% of average net profits towards CSR activities. The regulatory backing has pushed Indian firms to rethink their social engagement strategies (Sengupta & Bhowmick, 2020). CSR in India generally focuses on areas like education, health, rural development, and environmental sustainability. Firms that actively engage in CSR can gain competitive advantages such as better reputation, increased customer loyalty, and enhanced stakeholder trust (Mishra & Modi, 2013). From a financial perspective, firms with robust CSR initiatives tend to have lower risks and greater opportunities for sustainable growth, especially in sectors where customer or stakeholder scrutiny is high.

One of the keyways CSR moderates the relation of CAPEX and firm's performance is by acting as buffer against risks. CAPEX is inherently risky due to the uncertainty of returns and the long gestation periods involved. Firms that are heavily invested in CAPEX may face short-term financial instability. However, CSR can mitigate some of these risks by enhancing stakeholder trust and creating goodwill among customers, suppliers, and regulators. Research indicates that firms with strong CSR records are better equipped to deal with operational risks and regulatory challenges

(Porter & Kramer, 2006). In India, CSR initiatives focused on community development and environmental sustainability often generate goodwill, which can translate into more favorable market perceptions. CSR initiatives improve a company's goodwill, which further enhances its financial performance. For instance, firms that engage in CSR may find it easier to access capital, as investors are increasingly prioritising firms with strong social and environmental records (Moser & Martin, 2012). Thus, the study holds significance in understanding how CSR influences the CAPEX-Performance relationship that gives rise to the following research questions:

1. Does capital expenditure influence the firm's performance?
2. Does CSR moderate the CAPEX-Performance relationship?

Based on these research questions, the objectives developed for the study are:

1. To assess the influence of CAPEX on firms' performance.
2. To analyse the moderation impact of CSR on CAPEX-Performance relationship.

Further, study consists of literature review and hypothesis development in the second section, followed by research methodology, results and discussions, findings of the study, and finally the summary and conclusion.

## 2. Review of Literature

CAPEX have been recognised as a crucial factor in determining firm performance, as they contribute to enhancing a company's productive capacity, operational efficiency, and competitive edge (Abel & Eberly, 2011). In the context of India's rapidly growing economy, CAPEX is essential for companies to seize growth opportunities. However, while CAPEX can foster growth, it also presents certain risks. Overinvestment in CAPEX may stretch a company's financial resources, impacting its liquidity and short-term profitability (Gupta & Banga, 2020). Additionally, Chen et al. (2003) demonstrated that firms with higher CAPEX tend to see improvements in revenue growth, profitability, and return on investment (ROI), especially in industries like manufacturing, energy, and technology. According to Doms et al. (1995), investments in new technologies and equipment boost productivity and reduce operating costs, with CAPEX in technology and automation enhancing both labor and capital efficiency.

Moussa and Elmarzouky (2023) took a closer look at how CAPEX impacts ESG (Environmental, Social, and Governance) reporting, with a particular focus on the role of CG. They found that investing in CAPEX can actually boost ESG performance. Additionally, strong corporate governance helps companies communicate their ESG initiatives more effectively to stakeholders. Moser et al. (2019) assessed the interaction between market conditions, CAPEX, manufacturing elasticity, and production volume, providing insights into the effects of manufacturing investments. Their findings revealed that firms in process industries tend to follow market trends in their investments, influencing both short-term operations and long-term capacity growth. Taipi and Ballkoci (2015) examined CAPEX-Performance relationship in the Albanian construction sector, concluding that CAPEX and leverage ratio positively and significantly correlate with financial performance, while firm size is negatively correlated and not statistically significant. Kim et al. (2021) revealed a negative correlation between CAPEX and near-term earnings, while investigating the link between CAPEX and short-term earning performances for loss-making firms. Jaisinghani et al. (2018) analysed CAPEX-Performance relationship in the Indian automobile industry and reported a negative and persistent connection between CAPEX and performance.

Numerous research was conducted at how different factors, like investment choices and capital structure, affect company's performance. However, not many studies have really dug into the link between CAPEX and a firm performance. In this context, one of the hypotheses of the study can be proposed as:

*Hypothesis 1 ($H_{11}$). Capital expenditure of firms has a significant impact on performance.*

A lot of research revealed that corporate social responsibility (CSR) is linked to better performance for companies, like higher profits, return on assets (ROA), and rising stock prices. For instance, Orlitzky and his colleagues conducted a meta-analysis of 52 studies back in 2003 and found a strong connection between CSR and improved financial results. The study suggested that companies that prioritise CSR tend to do better financially. Similarly, Porter and Kramer introduced the idea of "Creating Shared Value" in 2006, arguing that CSR helps businesses set themselves apart by adding social and environmental value to their products and services. This not only gives them a competitive edge but also boosts their brand image and fosters customer loyalty.

On another note, research by Turban and Greening in 1997 highlighted that companies with a solid CSR reputation would attract more potential employees and enjoy better employee retention rates. Brammer and his team found in 2007 that when employees see their company as socially responsible, they tend to be more engaged and productive. Jo and Harjoto added to this in 2011, pointing out that companies with strong governance and CSR initiatives often outperform those that don't have these frameworks in place. So, it can be inferred that embracing CSR can really pay off in various ways for a business!

Gaba & Madhumathi (2023) observed that CSR and its relationship with value creation is still in its early stages compared to the more established links between CSR and financial performance. The evolving nature of value, influenced by globalisation and changing business landscapes, necessitates that managers adopt a more immediate and practical approach to address stakeholder expectations while also enhancing competitive advantages through reputation and investor value. Similarly, Kansal et al. (2018) discovered that CSR disclosures positively impact firm performance in India, particularly in sectors like manufacturing and energy. Their study attributed these better financial outcomes to the reputational advantages and operational efficiencies gained through CSR practices. Furthermore, Narwal and Sharma (2008) observed that Indian companies with well-established CSR practices generally outperform those without, as CSR fosters trust among stakeholders, leading to improved long-term financial returns on CAPEX. Kansal et al. (2018) also noted that the combination of CSR engagement and significant CAPEX investment has strong positive effect on firm performance in industries where environmental and social factors are critical, such as manufacturing, energy, and natural resources.

The association of CAPEX and firm performance is pretty intricate and can be influenced by several factors. One of these factors CSR. A study by Singh and Agarwal in 2019 found that CSR initiatives can actually boost the positive impact of CAPEX on firm performance, particularly in industries where social and environmental issues are important. Their findings showed that companies with strong CSR programs often enjoy better long-term returns on their investments because they build stronger relationships with their stakeholders and enhance their social capital.

While there are various studies that have looked at CSR as a moderating factor in performance-related research, the researcher noticed a gap. Specifically, there seems to be a lack of studies focusing on CSR spending as a moderating element in the correlation linking CAPEX and firm performance, especially from an Indian perspective. Since Companies Act 2013 requires certain Indian firms to spend on CSR, it’s crucial to understand how this regulation might influence the role of CSR in the CAPEX-performance dynamic. In this context, the second hypothesis for the study can be proposed as:

*Hypothesis 2 ($H_{12}$). Corporate Social Responsibility moderates the effect of capital expenditure on firm performance.*

## 3. Research Methodology

The study focused on the Nifty 200 companies over the period from 2016-17 to 2023-24. The time period under study was selected on the basis of the period of implementation of Ind AS, which ensures data consistency and reliability. The financial institutions were excluded from the analysis since they have different accounting practices and reporting structures that could lead to skewed results. Further, based on availability, a final sample of 31 companies was selected, which gives a total of 248 observations across different years. The data were gathered from the companies' published reports and the CMIE Prowess database. The variables taken for the study are described as below:

**Table 1: Variable Description**

| Variable | Description |
|---|---|
| **ROA** | Return on Assets (ROA) is a financial ratio that measures a company's profitability relative to its total assets. It is calculated as: (Net Operating Income - Taxes) / Average Total Assets. |
| **Tobin's Q** | It is a financial ratio that measures the market value of a firm relative to the replacement cost of its assets. It is calculated as: Ratio of (Equity at market value & Liabilities at book value) to Total Assets of the Firms (Market performance Indicator). |
| **CAPEX** | Capital expenditure (CAPEX) refers to a firm's spending on acquiring, upgrading, or maintaining long-term assets. It is calculated as: Log of Sum of Non-Current Assets including Tangible assets, Intangible assets, and financial assets. |
| **CSR** | CSR expenditure of a firm refers to the total amount spent by a company on its Corporate Social Responsibility (CSR) activities, as mandated by law. This expenditure is typically calculated as 2% of the company's average net profit over the preceding three financial years. It is calculated as: Log of Total Amount of CSR spent during the year. |
| **Size** | Total Assets of the firms It is calculated as: Log of Total Assets. |
| **Leverage** | It shows the Debt to Equity ratio of the firms. It is a financial leverage ratio that compares a company's total debt (liabilities) to its total shareholder equity. It indicates the extent to which a company relies on debt versus equity to finance its operations. It is calculated as: Debt to Equity ratio. |
| **Sales Growth** | It refers to the percentage increase in a company's sales revenue over a specific period, typically a year. It's a key indicator of a company's financial health and success, reflecting its ability to generate more revenue from selling goods or services. It is calculated as: Rate of increase/decrease of total sales. |

Source: Author's compilation.

For analysis, the study used panel regression, and to determine whether to use fixed-effect or random-effect models, Hausman test was conducted. Significance tests were also performed to understand how strongly the dependent variable is influenced. Each of the hypotheses is examined through four equations that form the backbone of our research model. For the developed hypotheses 1 and 2, the respective Research Models (i) & (ii) and (iii) & (iv) are as below:

$$\textbf{ROA}_{it} = \beta_0 + \beta_1 CAPEX_{it} + \beta_2 SIZE_{it} + \beta_3 LEVERAGE_{it} + \beta_4 SALESGROWTH_{it} + \varepsilon_{it} \text{ ........ } \textbf{(i)}$$

$$\textbf{Tobin's Q}_{it} = \beta_0 + \beta_1 CAPEX_{it} + \beta_2 SIZE_{it} + \beta_3 LEVERAGE_{it} + \beta_4 SALESGROWTH_{it} + \varepsilon_{it} \text{........} \textbf{(ii)}$$

$$\textbf{ROA}_{it} = \beta_0 + \beta_1 CAPEX_{it} + \beta_2 CAPEX{*}CSR_{it} + \beta_3 SIZE_{it} + \beta_4 LEVERAGE_{it} + \beta_5 SALESGROWTH_{it} + \varepsilon_{it} \text{ ........ } \textbf{(iii)}$$

$$\textbf{Tobin's Q}_{it} = \beta_0 + \beta_1 CAPEX_{it} + \beta_2 CAPEX{*}CSR_{it} + \beta_3 SIZE_{it} + \beta_4 LEVERAGE_{it} + \beta_5 SALESGROWTH_{it} + \varepsilon_{it} \text{ ........ } \textbf{(iv)}$$

## 4. Results and Discussion

This study attempted to analyse how capital expenditures (CAPEX) impact the performance of 31 companies in the NIFTY 200 index, using data from 2016-17 to 2023-24. An attempt was made to understand how CAPEX influences key performance metrics like Return on Assets (ROA) and Tobin's Q. It was also examined that how corporate social responsibility (CSR) might play a role in shaping the correlation of CAPEX and firm's overall performance.

## 4.1 Impact on Return on Assets (ROA)

To determine whether a fixed-effects model or a random-effects model was more suitable for our analysis, Hausman test was conducted. The findings for ROA showed a statistically significant result, with a p-value of 0.0179, as shown in Table 2. This indicates that the fixed-effects model is the better choice for this analysis.

**Table 2: ROA Hausman Test**

| Test Summary | Prob. |
|---|---|
| Cross-section random | 0.0179 |

Source: Author's compilation.

Table 3 gives the results of our fixed-effects regression analysis, which looks at how CAPEX affects ROA while considering other factors like total assets (SIZE), the debt-to-equity ratio (leverage), and sales growth. The results reveal a noteworthy negative relationship between CAPEX and ROA ($\beta = -0.287$, SE = 0.093, t = -3.101, p = 0.002). This suggests that as CAPEX increases, ROA tends to decrease.

**Table 3: Impact of Capital Expenditure on ROA**

| Variables | Coeff. | Std. Errors | t-Stats | P-value |
|---|---|---|---|---|
| **Intercept** | 0.523 | 0.125 | 4.175 | 0.001 |
| **CAPEX** | -0.287 | 0.093 | -3.101 | 0.002 |
| **Size** | 0.011 | 0.049 | 0.203 | 0.839 |
| **Leverage** | 0.411 | 0.114 | 3.599 | 0.001 |
| **Salesgrowth** | 0.084 | 0.051 | 1.652 | 0.101 |
| | | **Effect Specification** | | |
| **R-squared** | | | | 0.547 |
| **Adjusted R-squared** | | | | 0.475 |
| **F-stats** | | | | 7.571 |
| **Probability (F-stats)** | | | | 0.001 |
| **DW stats** | | | | 1.704 |

Source: Author's compilation.

It was found that SIZE and SALES GROWTH of companies don't really have a significant impact on Return on Assets (ROA) in the model. On the other hand, Leverage stands out with a strong positive relationship to ROA. This suggests that companies with higher leverage often see better returns on their assets. Overall, the model does a decent job, explaining about 54.7% of the variation in ROA (with an $R^2$ of .547). On adjustment for the number of predictors, the results get an adjusted $R^2$ of .475, which indicates a good fit. The F-stats of 7.571 (with a p-value less than .001) shows that our independent variables are collectively significant. Plus, the Durbin-Watson statistic is at 1.704, which is comfortably within the acceptable range of 1.5 to 2.5, suggesting there aren't any autocorrelation issues.

## 4.2 Impact on Tobin's Q

Moving on to Tobin's Q, a Hausman test was conducted to determine whether random-effect model or fixed-effect model would be more suitable for the analysis of how CAPEX affect this important measure of firm performance. The results yielded a p-value of 0.033 for the cross-section random effect, which is statistically significant at the 5% level ($p < .05$), as shown in Table 4. This indicates rejection of the random-effect model and favouring the fixed-effect model for the analysis.

**Table 4: Tobin's_Q_Hausman Test**

| Test Summary | Prob. |
|---|---|
| Cross-section random | 0.033 |

Source: Author's compilation.

Table 5 gives the results from fixed-effect regression analysis, which examines how CAPEX, along with some control variables like total assets (SIZE), the debt-to-equity ratio (leverage), and sales growth, impacts Tobin's Q. The findings indicate that CAPEX has a significant negative effect on Tobin's Q ($\beta$ = -0.306, SE=0.082, t = -3.720, p < .001). In simpler terms, as companies increase their CAPEX, their market valuation tends to drop. It seems like the market might interpret higher CAPEX as a sign of inefficiency or a delay in seeing returns, which can lead to a decrease in Tobin's Q.

**Table 5: Impact of Capital Expenditure on Tobin's Q**

| Variables | Coeff | Std. Errors | t-Stats | P-value |
|---|---|---|---|---|
| **Intercept** | 0.747 | 0.112 | 6.699 | 0.001 |
| **CAPEX** | -0.306 | 0.082 | -3.719 | 0.001 |
| **Size** | -0.021 | 0.044 | -0.462 | 0.644 |
| **Leverage** | 0.226 | 0.102 | 2.225 | 0.027 |
| **Salesgrowth** | -0.027 | 0.045 | -0.592 | 0.554 |
| | | **Effects Specification** | | |
| **R squared** | | | | 0.683 |
| **Adjusted R squared** | | | | 0.633 |
| **F-stats** | | | | 13.513 |
| **Probability (F-stats)** | | | | 0.001 |
| **DW Stats** | | | | 1.587 |

Source: Author's compilation.

The model explains 68.3% of the variation in Tobin's Q, with an adjusted $R^2$ of .633, indicating a strong fit. The F-statistic (13.513, $p$ < .001) confirms the joint significance of the predictors. The Durbin-Watson statistic (1.587) indicates that there exists acceptable autocorrelation, since the value is within an acceptable range of 1.5 - 2.5. In conclusion, CAPEX and leverage significantly impact Tobin's Q, while firm size and sales growth do not show substantial influence on market valuation in this model.

## 4.3 Moderation effect of CSR

CSR is examined for significantly moderating the relationship between CAPEX and firm performance. The results in Table 6 reveal a significant interaction effect in both the ROA (p value = 0.009) and Tobin's Q (p value = 0.033) models, having the interaction coefficient for ROA in Model (iii) as 0.08999, while for Tobin's Q in Model (iv) as 0.05171, demonstrating how CSR spending positively augments the CAPEX to result in better performance.

**Table 6: Moderating Effect of CSR on CAPEX-Performance Relationship**

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| **CSR*CAPEX on CAPEX-ROA Relationship** | 0.089989 | 0.034076 | 2.640858 | 0.0089 |
| **CSR*CAPEX on CAPEX-Tobin's Q Relationship** | 0.051710 | 0.030639 | 1.687710 | 0.0329 |

Source: Author's compilation.

Firms with higher CSR involvement can offset some of the negative impact of CAPEX on firm profitability, potentially by enhancing stakeholder relations or improving operational efficiency through sustainable practices. Again, firms engaging in CSR may improve their market valuation in the presence of higher CAPEX, perhaps due to enhanced reputation or long-term strategic benefits.

## 5. Findings

This study researched into how CAPEX influences a company's performance, particularly looking at financial returns like ROA and market valuation through Tobin's Q. It also examined the role of CSR in this mix. The various regression analysis provide some interesting insights into how CAPEX and firm outcomes interact, along with the impact of CSR.

One of the key takeaways is that CAPEX can actually have a significant negative effect on ROA. In simpler terms, when companies pour a lot of money into capital investments, it doesn't necessarily mean they'll see better returns on their assets right away. In fact, it can sometimes lead to a dip in profitability in the short term. This might happen because the benefits of these investments take time to kick in, especially when they're aimed at long-term assets. Initially, these spending sprees can increase costs without a corresponding boost in revenue or profits, which can lead to a temporary drop in ROA.

The study also shows that CAPEX tends to negatively affect Tobin's Q, indicating that the market often views high capital spending unfavorably in terms of a company's value. Investors may interpret these hefty expenditures as a sign of inefficiency or heightened risk, particularly if they're unsure about when the returns will start rolling in. This skepticism can result in a lower market valuation compared to the company's assets.

On a brighter note, the research highlights how CSR activities can help moderate the relationship between CAPEX and both ROA and Tobin's Q. It turns out that engaging in socially responsible practices can actually improve a company's performance, even if there are some short-term dips in profitability due to increased capital spending. Companies that are more committed to CSR often enjoy better relationships with stakeholders, a stronger reputation, and improved operational efficiencies. This can help offset some of the immediate financial pressures associated with CAPEX. Plus, CSR initiatives might even soften the negative impact of CAPEX on market valuation by enhancing the company's reputation or signalling to investors that there are long-term strategic benefits on the horizon. Firms that prioritise CSR tend to be viewed as more sustainable and forward-thinking, which can lead to a more favourable perception in the market, even when they're investing heavily in capital.

Indian companies can improve performance by prioritising strategic investments, focusing on sustainability, and aligning CSR initiatives with business goals. By integrating CSR with business strategy and measuring impact, companies can create shared value and contribute to sustainable development. This approach enhances stakeholder value and drives long-term growth.

Policy Implications for Firms: In line with this approach, business firms should reassess capital expenditure priorities to ensure alignment with business goals and conduct thorough cost-benefit analyses for projects. They should also focus on investments that drive long-term value creation. By adopting these strategies, companies can optimise their capital allocation, reduce risks, and improve their overall performance.

Policy Implications for Investors: Investors play a crucial role in ensuring companies make informed, value-driven decisions. To support this, investors should carefully examine companies' capital expenditure choices to assess their alignment with business strategy and evaluate the expected return on investment (ROI) and long-term value creation potential. By being transparency on capital allocation and vigilant, investors can make informed decisions and hold companies accountable for efficient capital utilisation.

## 6. Conclusion

CAPEX plays a crucial role in a company's success by driving growth, improving operational efficiency, and fostering innovation. The link between CAPEX and a company's performance is quite intricate but incredibly important. When companies invest wisely in capital projects, they can boost their revenue, streamline operations, and gain a competitive edge, which ultimately leads to better profits and higher market valuation.

This study conducted a deeper analysis of how CAPEX affects firm performance, specifically focusing on financial returns like ROA and Tobin's Q. The role played by CSR, as a moderating factor, was also studied. The findings revealed that CAPEX tends to have a significant negative impact on both ROA and Tobin's Q. However, companies that are more engaged in CSR activities seem to buffer these negative effects. In other words, those with strong CSR initiatives can improve their financial performance and market value, suggesting that CSR plays a strategic role in managing the challenges that come with hefty capital investments. It also helps build better relationships with stakeholders and enhances the company's reputation.

Looking ahead, there are plenty of avenues for future research. While this study focuses on CSR as a moderating factor, it would be worthwhile to explore other influences, such as innovation or governance practices, that might strengthen the connection between CAPEX and company outcomes. Additionally, examining how CSR and CAPEX interact in different regional or international settings could shed light on how local market dynamics or regulatory environments affect firm performance. By broadening the scope of research in these areas, scholars can better understand how CAPEX impacts company performance under various conditions and how strategic initiatives like CSR can be used to optimise results.

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Promoting Research

# Do Sustainability Practices Improve Share Price of Top Indian Companies? Empirical Evidence Using System GMM

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**Abstract:** Corporate sustainability has become a major concern of modern businesses. Nowadays, a corporation's performance is not only measured with traditional financial metrics but also from the perspective of sustainability. This study aims to examine how corporate sustainability affects the stock prices of top Indian firms from 2015–16 to 2021–22. Using the non-probability judgmental sampling method, the top one hundred and seventeen Indian companies, as per their market capitalisation, have been chosen as the final sample. It uses the dynamic panel data method for empirical estimation. The findings indicate that the one-year lag of the Composite ESG score, along with Environmental, Social, and Governance scores, has a positive influence on the share prices of the sample companies. Therefore, improvement in sustainable activities can increase the share price of top Indian companies.

## 1. Introduction

These days, corporate social responsibility is one of the most important concerns for businesses globally (Alshannag & Basah, 2016). Concerns about climate change have raised interest in sustainability and environmental problems. Over the last several decades, policymakers, regulators, investors, business owners, academics, researchers, and several other stakeholders have provided a lot of attention to sustainable development. In 2004, the UNGC introduced the environmental, social, and governance (ESG) concept, a useful framework for advancing sustainable development. Traditionally, ESG is a non-financial evaluation technique. Businesses have been aggressively integrating ESG concepts into their operations in order to address global issues regarding sustainable development. India's prime minister said during the COP 26 conference that the nation will meet its goals to have half of its energy derived from renewable sources within 2030, as well as to reach net zero carbon emissions within 2070. Corporate enterprises in India are crucial to achieve these goals. Additionally, Indian companies are coordinating their sustainability initiatives with both the nation's sustainable development agenda and international trends. Because businesses with good governance, social, and environmental standards are attracting more and more investors (Bhattacharya & Sharma, 2019). Though, there is a common belief that CSR initiatives are expensive and may conflict with the objective of generating profits for shareholders (Odeh et al., 2019), but around the world, top companies focus on investing in CSR initiatives to improve their reputation, firm value, minimise cost of capital, etc. Conceptually, the term 'sustainability' and 'CSR' are quite different. According to Hopkins (2017) CSR is recognised as an umbrella concept that encourages responsible processes those must be followed by businesses. Whereas, sustainability refers to some goals that should be followed by firms. However, in various literature these terms have been used interchangeably.

On the other hand, the financial performance of a business is considered as the main criteria to make prudent investment decisions. But recently, apart from financial indicators, some non-financial factors, such as ESG activities or sustainability practices of businesses, are also being considered by the investors and fund managers. Many studies support the link of corporate sustainability performance with company's long-term growth. As a result, the majority of investors consider ESG aspects when making investment decisions. As ESG standards have been more widely accepted by businesses and investors, academics from across the globe have investigated the various aspects of corporate sustainability.

Nowadays, investors' preference towards sustainability is increasing day by day. ESG considerations have grown more significant as investors attempt to combine their financial rewards with environmental and social obligations. Firms are incorporating ESG factors into various elements of their operations to improve their credibility and obtain a competitive advantage in the marketplace. There is evidence that the ESG factors are a source of risk to business, and have the ability to influence the financial returns.

Due to the absence of consistent findings regarding how the corporate financial performance is impacted by sustainable practice, the problem statement of the present study can be stated as "To analyse the influence of corporate sustainability practices on stock prices of top listed companies in India". It will analyse whether firms that emphasise ESG factors have better stock prices in comparison to firms that do not focus on ESG factors.

One of the world's biggest economies and a country that is expanding rapidly, India has specific issues in the areas of government, society, and the environment. Ministry of Corporate Affairs (MCA) under Government of India (GOI) issued National Voluntary Guidelines (NVGs) regarding Social, Environmental and Economic accountabilities for corporate organisations on 2011 as adaptation of sustainable practices among Indian corporates. In May 2021, the Business Responsibility and Sustainability Report (BRSR) was introduced by the Securities and Exchange Board of India (SEBI) to outline sustainability-related reporting obligations for the top thousand listed firms in India as per their market capitalisation. This BRSR replaced the Business Responsibility Report (BRR). The disclosure requirement of BRSR, which came into effect from F.Y. 2022–2023, was seen as a step toward bringing the requirements of sustainability reporting along with traditional financial reporting of Indian companies. Given the growing emphasis on accountability, transparency, and ethical behaviour among Indian companies, it is essential to comprehend the connection between their sustainability practices and financial performance.

The remaining portion of this study is organised as follows: Section II evaluates the associated literature and highlights the research gap. Section III addresses the research objectives and section IV provides hypotheses. Data and methods are discussed in Section V. Section VI addresses empirical evidence and gives additional insights. Finally, the study ends with section VII.

## 2. Review of Literature

Numerous studies have been carried out to study the association of a firm's corporate sustainability practices with its financial performance. In order to help to identify research gaps and, thus, frame the research objectives and hypotheses of the present study, the next section offers reviews of some of these studies.

### 2.1. Theoretical Viewpoints

It is still a complex issue today with some arguing for social responsibility while others prioritise maximising shareholder value. Friedman and Freeman debated whether companies should only focus on financial gain or also consider their impact on society. In this regard, two academic theories are much important. One is shareholders theory of Milton Friedman (1970), who proposed that voluntary organisations and taxes should support society rather than businesses. This theory suggests that a firm's primary goal must be to enhance its shareholders' wealth. Another is, stakeholders theory, popularised by Freeman (1984). It said that organisations had to think beyond maximising shareholders' wealth and should consider to maximise the values of all stakeholders.

### 2.2. Significance of Sustainability Reporting

Currently, like publishing a company's financial performance, its CSR or sustainability disclosures can play a vital part in investment decisions of investors (Hassel et al. 2005; Dhaliwal et al. 2011). If investors possess adequate information on future liabilities, they could demand a greater rate of earnings for their investment. Managers can use voluntary disclosure to update shareholders on the social and environmental initiatives of the company (Healy & Palepu, 2001).

### 2.3. Linkage between Share Price and Sustainability

Al-Tuwaijri et al. (2004) studied that companies' environmental performance was positively associated with their annual returns, suggesting that investors considered environmental factors during their investment choices. The stock prices of South African firms were shown to be positively correlated with CSR disclosure as studied by De Klerk and De Villiers (2012). Reverte (2014) revealed that CSR disclosure has an effect on Spanish firms' share prices both directly and indirectly. A study on European banks has shown that the release of sustainability reports has a favourable impact on stock prices (Carnevale & Mazzuca, 2014). Furthermore, De Klerk et al. (2015) studied the link of share price with corporate social responsibility (CSR) disclosure of the largest UK corporations and found that a higher degrees of CSR disclosure related to higher share prices. Therefore, the majority of the research linked to this topic indicated a positive and substantial association. Therefore, most of the studies relating to this area found a positive and significant relationship.

Again, a few studies revealed a negative and inconclusive association. Hassel et al. (2005) discovered that Swedish listed firms with good environmental performance ratings had considerably less market values, indicating that investors did not put a high value on environmental performance. According to Bolton and Kacperczyk (2021), stock returns are often lower for US companies that have high ESG ratings.

Though most of the research demonstrates that improvement in sustainable practices by enterprises enhances their share prices, there is an argument on whether these correlations are constant across various sectors and nations. 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 various corporate sustainability pillars affect the share price of top Indian firms.

Based on the identified research gap, the objectives are specified as follows:
(i) To examine how the overall corporate sustainability affects the share prices of the top listed companies in India
(ii) To analyse how the separate corporate sustainable activities, namely environmental, social and governance, influence the share prices of top listed companies in India.

The following hypothesis has been generated to respond to the primary research question:
**$H_{1:}$** There is significant impact of corporate sustainability (ESG) score on share price of top Indian companies.
It is further divided into the three parts listed below:
**$H_{1a:}$** There is significant influence of Environmental (E) score on share price of top Indian companies.
**$H_{1b:}$** There is significant influence of Social (S) score on share price of top Indian companies.
**$H_{1c:}$** There is significant influence of Governance (G) score on share price of top Indian companies.

## 3. Data and Methodology

### 3.1. Sample and Data

Using non probability based judgmental sampling method, out of India's Top two-hundred companies as per their market capitalisation, one hundred and seventeen companies have been included in the final sample due to accessibility to appropriate data. The study relies on secondary data only. Required financial as well as non-financial data have been retrieved from Capitaline and Bloomberg databases, respectively. ESG performance scores computed by the Bloomberg have been used as proxy for corporate sustainability. The mandatory provisions for CSR came into existence in India from F.Y. 2014-15 and thereafter the societal activities among the Indian corporates have improved. Therefore, the study period has been fixed from 2015-16 to 2021-22, which is beyond the F.Y. 2014-15 to capture the impact of sustainability more accurately.

## 3.2.Variables and Models

To meet the research objectives, the following dependent, independent and control variables mentioned in Table 1 have been chosen as proxy. The independent variables are measured with 0 to 100 scale. One-year lag of the independent variables has been selected as the current year's sustainability performance may impact the share prices of the next year.

**Table 1: Variable Description**

| Variable Type | Variable Name | Description |
|---|---|---|
| Dependent | BSE Market Price of a Share (SP) at the end of a F.Y. | Share Price. |
| Independent | 1-year lag of ESG Score published by Bloomberg (ESG_L1) | Overall corporate sustainable activities. |
| | 1-year lag of Environmental Score published by Bloomberg (E-Score_L1) | Environmental activities. |
| | 1-year lag of Social Score published by Bloomberg (S-Score_L1) | Social activities. |
| | 1-year lag of Governance Score published by Bloomberg (G-Score_L1) | Governance activities. |
| Control | Return on Assets (ROA): Measured as EBIT ÷ Total Assets | Overall Profitability |
| | Total Assets (TA): Computed as natural log of the total assets. | Size |
| | Debt to Assets Ratio (Lev): Measured as Total Debt ÷ Total Assets. | Leverage |
| | Current Ratio (Liq): Measured as Current Assets ÷ Current Liabilities. | Liquidity |

Source: Authors' compilation.

The panel data analysis approach is applied to achieve the research objectives. 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 assists in adjusting for individual heterogeneity (Baltagi, 2005). The dynamic panel regression method has been used here to handle heterogeneity and endogeneity issues.

To examine how the overall corporate sustainability affects the share prices of top listed companies in India, the following model has been formed:

$$SP_{i,t} = \alpha_0+\alpha_1 SP_{i,\,t-1}+ \alpha_2 ESG\_L1_{i,t}+ \sum\alpha_j ControlVariables_{i,\,t}+ \varepsilon_{i,\,t} \ldots\ldots\ldots (1)$$

Again, the following three models has been employed to gauge the effect of the three pillars of corporate sustainability on the share price:

$$SP_{i,t} = \alpha_0+\alpha_1 SP_{i,\,t-1}+ \alpha_2 E\text{-}Score\_L1_{i,\,t}+ \sum\alpha_j ControlVariables_{i,\,t}+ \varepsilon_{i,\,t} \ldots\ldots\ldots (2)$$

$$SP_{i,t} = \alpha_0+\alpha_1 SP_{i,\,t-1}+ \alpha_2 S\text{-}Score\_L1_{i,\,t}+ \sum\alpha_j ControlVariables_{i,\,t}+ \varepsilon_{i,\,t} \ldots\ldots\ldots (3)$$

$$SP_{i,t} = \alpha_0+\alpha_1 SP_{i,\,t-1}+ \alpha_2 G\text{-}Score\_L1_{i,\,t}+ \sum\alpha_j ControlVariables_{i,\,t}+ \varepsilon_{i,\,t} \ldots\ldots\ldots (4)$$

Here, intercept is $\alpha_0$, composite error term is $\varepsilon_{i,\,t}$, whereas, i implies firm, and t refers to year for each 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 one-step system GMM using xtabond2 command (Roodman, 2009).

## 4. Results and Discussion

The descriptive statistics of the variables are shown in Table 2. The mean ESG score of the sample companies is 41.41%, which indicates more activities are required by Indian companies on ESG front. Again, among the three separate pillars of corporate sustainability, the mean of governance score (79.16%) is the highest followed by the score of social dimensions (27.385%). It implies that adherence to good governance practices is major priority in Indian corporate sector (Mondal & Mitra, 2024). The reason may be the existence of a mandatory regulatory framework for governance-related factors. The poor mean value of social score indicates that Indian firms should be encouraged to practice social disclosures to meet the stakeholders' requirements. Lastly, the average score for the environmental initiatives has come out to be lowest as 23.857%, with highest value of dispersion among sustainability variables; indicating more consistent efforts are required by the Indian corporates to carry out policies and practices on green management.

**Table 2: Descriptive Statistics**

| Variables | Observations | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| **SP** | 819 | 2055.48 | 6797.761 | 3.11 | 82218.701 |
| **ESG_L1** | 702 | 41.41 | 11.288 | 19.274 | 76.139 |
| **E-Score_L1** | 702 | 23.857 | 21.069 | 0 | 77.288 |
| **S-Score_L1** | 702 | 27.385 | 11.9 | 0 | 70.042 |
| **G-Score_L1** | 702 | 79.16 | 8.641 | 27.152 | 98.615 |
| **ROA** | 819 | 16.94 | 13.249 | -20.495 | 77.852 |
| **TA** | 819 | 9.852 | 1.501 | 6.406 | 13.787 |
| **Lev** | 819 | .883 | 2.415 | 0 | 13.205 |
| **Liq** | 819 | 4.982 | 8.775 | .277 | 57.728 |

Source: Authors' compilation.

The correlation between the consolidated ESG score and its constituent parts has been shown to be more than 0.5; that is, the values between the environmental, social, and governance scores and ESG are 0.879, 0.876, and 0.556, respectively. Therefore, several regression models have been conducted in order to prevent multicollinearity among independent variables.

**Table 3: Pairwise correlations**

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **(1) SP** | 1 | | | | | | | | |
| **(2) ESG_L1** | -0.088* (0.019) | 1 | | | | | | | |
| **(3) E-Score_L1** | -0.068 (0.073) | 0.879* (0.000) | 1 | | | | | | |
| **(4) S-Score_L1** | -0.132* (0.000) | 0.786* (0.000) | 0.699* (0.000) | 1 | | | | | |
| **(5) G-Score_L1** | 0.003 (0.928) | 0.556* (0.000) | 0.394* (0.000) | 0.293* (0.000) | 1 | | | | |
| **(6) ROA** | 0.030 (0.397) | -0.106* (0.005) | -0.093* (0.014) | -0.028 (0.456) | -0.191* (0.000) | 1 | | | |
| **(7) TA** | -0.127* (0.000) | 0.247* (0.000) | 0.249* (0.000) | 0.203* (0.000) | -0.023 (0.536) | -0.096* (0.006) | 1 | | |
| **(8) Lev** | -0.084* (0.016) | -0.044 (0.243) | -0.036 (0.341) | 0.068 (0.074) | -0.269* (0.000) | 0.544* (0.000) | 0.308* (0.000) | 1 | |
| **(9) Liq** | -0.069* (0.047) | -0.175* (0.000) | -0.208* (0.000) | -0.069 (0.070) | -0.204* (0.000) | 0.361* (0.000) | 0.318* (0.000) | 0.686* (0.000) | 1 |

Source: Authors' compilation.

*Note: * shows significance at $p < 0.05$*

Table 4 displays the outcomes of the one-step System GMM. The result shows that the regression coefficient of SP to ESG_L1 is 13.473 that is significant at 1% level. Therefore, the outcome validates hypothesis H1, which states that the share prices of the Indian companies are positively and significantly impacted by overall corporate sustainability. Further, the regression coefficients of SP to E-Score_L1, S-Score_L1 and G-Score_L1 are 4.999, 5.564 and 0.478, respectively, significant at 1% level. Consequently, the share price of the Indian firms is positively impacted by Environmental, Social, and Governance initiatives in a statistically significant way. Out of the four control variables profitability, firm size and liquidity have positive and leverage has negative impact on share price and all these are also significant at 1% level. Hansen test and autocorrelation i.e. AR (2) test imply the absence of endogeneity and autocorrelation issues respectively in the model, as both of them accept the research hypothesis.

Though to identifying the reasons behind the results is beyond the scope of this study, but previous literature has provided some insight regarding it. Overall, the findings show that firms with strong ESG performance tend to have higher share prices than those with poor ESG performance. In fine, the findings suggest that companies with strong ESG performance tend to have higher share prices compared to those with weak ESG performance. However, this influence of ESG considerations on share prices might vary by industry to industry and country to country.

**Table 4: Regression Results**

| **Variables** | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| **SP_L1** | 0.879*** | 0.892*** | 0.888*** | 0.890*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **ESG_L1** | 13.473*** | | | |
| | (0.000) | | | |
| **E-Score_L1** | | 4.999*** | | |
| | | (0.000) | | |
| **S-Score_L1** | | | 5.564*** | |
| | | | (0.000) | |
| **G-Score_L1** | | | | 0.478*** |
| | | | | (0.027) |
| **ROA** | 6.432*** | 5.527*** | 5.433*** | 3.898*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **TA** | 50.346*** | 40.064*** | 18.767*** | 54.525*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Lev** | -82.557*** | -71.934*** | -70.969*** | -71.821*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Liq** | 8.462*** | 7.149*** | 7.143*** | 9.229*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Constant** | -1033.63*** | -502.64*** | -318.736*** | -546.818*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| **Hansen test** | 10.130 | 14.890 | 18.870 | 11.890 |
| *Prob> chi2* | (1.000) | (0.986) | (0.925) | (0.998) |
| **AR (2)** *P value* | 0.242 | 0.244 | 0.243 | 0.244 |
| **Number of obs** | 702 | 702 | 702 | 702 |

*Note: *** p<0.01, ** p<0.05, * p<0.10*

Source: Authors' compilation.

## 5. Conclusion

Corporate sustainability has become a major concern of modern businesses. Nowadays, a corporation's performance is not only measured with traditional financial matrices but also from the perspective of sustainability. Keeping this in mind, the major purpose the study has been established for evaluating the effect of corporate sustainability on share prices of top Indian corporations throughout the period from 2015-16 to 2021-22. It uses ESG scores provided by Bloomberg as the proxy of corporate sustainability performance of the sample companies whereas, their year-end share prices in BSE were considered as the dependent variable. In addition, four control variables have been used to measure the profitability, size, leverage, and liquidity of the companies. The empirical tests revealed that one-year lag of composite ESG score and individual Environmental, Social, and Governance scores have positive and statistically significant impact on share price. It is in line with the studies of Al-Tuwaijri et al. (2004), De Klerkand and De Villiers (2012), Carnevale and Mazzuca

(2014), De Klerk et al. (2015), and thus supports the stakeholders theory. Therefore, this study reveals that top Indian firms with superior sustainability policies in the present year may attain a higher share price in the coming year.

The study has substantial implications or suggestions for various stakeholders. Firstly, investors may utilise ESG scores for investment decisions. Secondly, the policymakers and regulators can use initiatives to encourage firms to adopt sustainable practices. Thirdly, adopting ESG principles may also help companies as a result of improved market capitalisation and share price with favourable sustainable performance. Lastly, the results will add to the existing body of knowledge in the area of impact assessment of ESG in India and have useful ramifications for Indian investors, legislators, and business leaders.

It is necessary to recognise the several drawbacks that this research may have. Firstly, the sample size examined is quite small. The findings may change if a bigger sample is used, and the results may not be as broadly applicable to other nations due to sample selection criteria. Second, the research could not have taken into consideration all the variables that influence share price, such investor attitude or macroeconomic circumstances. Again, not all factors from prior research could be included. Third, the findings may be affected by the economic downturn since the data used spans the years 2020–2022, which includes a time of worldwide lockdown forced on by the COVID-19 pandemic. Fourth, Bloomberg's ESG data is the only source of information used in this research. Scores are calculated using a variety of criteria by the main ESG rating agencies. As a consequence, accessing data from a different organisation might result in different analytical outcomes. Moreover, as per SEBI's new regulations for ESG rating providers (ERPs) w.e.f. 12$^{th}$ July, 2023 (SEBI, 2023), the Bloomberg is still not registered itself in SEBI as an ERP. Therefore, the ESG data beyond 2021-22 could not be considered in this study due to its inaccessibility. Additional research that addresses these constraints may provide more reliable findings.

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Promoting Research

# R&D Intensity and Corporate Borrowings in Indian Pharmaceutical Firms

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**Abstract:** This study investigates the influence of research and development (R&D) intensity on corporate borrowing behaviour in the Indian pharmaceutical firms. Taking a sample of 97 pharmaceutical firms collected from the Prowess database covering a period of 10 years from 2015 to 2024, the regression evidence shows a significant negative impact of R&D intensity on corporate borrowings. This indicates that firms with higher R&D investments tend to rely less on debt financing. This outcome supports the pecking order theory, suggesting that firms choose internal financing over external financing due to the higher cost and elevated risk associated with R&D activities, as R&D is intangible and non-collateralisable. Additionally, firm size and cash flow negatively influence borrowings, emphasising the importance of internal sources in financing innovation. The findings contribute to the literature on corporate finance and pharmaceutical firms, highlighting the need for alternative financing mechanisms to support innovation-driven growth in emerging economies like India. This study also provides a more nuanced approach to corporate financial planning, where innovation goals are integrated into financial decision-making.

## 1. Introduction

In the current dynamic and competitive business environment, businesses are increasingly confronted with rapid technological advancements, shifting consumer expectations, regulatory changes, and global uncertainties (Gupta, 2014). These factors collectively necessitate continuous reassessment of strategies, processes, and business models (Pusparini et al., 2020). The ability to adapt to change is no longer optional but a critical determinant of structural resilience and long-term success (Duchek, 2020). Proactive adoption of innovation, digital transformation, and agile practices enables firms to respond effectively to emerging challenges and capitalise on new opportunities (Akpan et al., 2022; Duchek, 2020; Wang et al., 2022). In this context, embracing change is essential for maintaining competitiveness, ensuring operational efficiency, and sustaining growth. Research and development investment has emerged as a key driver of sustainable business performance (Wu et al., 2019). Now it is increasingly acknowledged as a fundamental pillar for fostering innovation, securing competitive advantage, and driving the long-term growth and sustainability (Coad & Rao, 2010; Hall, 2011). Today's rapidly evolving global economy, characterised by technological disruption, consumer sophistication, and intensified competition, firms are under pressure to innovate new products, processes, and services, to grow and stay sustainable in the transitional business environment (Brem et al., 2023; Nambisan et al., 2019). R&D is the engine through which firms develop new products, improve existing offerings, and enhance operational processes (Zaman & Tanewski, 2024). Firms allocate resources to R&D activities with the expectation that such expenditures will foster the development of new products, processes, and technologies, ultimately translating into increased sales and market share (Hagedoorn & Wang, 2012).

Within the constantly shifting macroeconomic framework, conventional indicators such as gross domestic product (GDP), exchange rates, inflation, and employment levels remain fundamental determinants of economic development (Guru & Yadav, 2019; Mensi et al., 2020). However, within the evolving paradigm of a digitally driven and innovation-centric economy, R&D investment has gained significant prominence as a catalyst for sustainable economic growth. Recent scholarly studies emphasise the critical role of R&D in enhancing national competitiveness, fostering innovation, and ensuring long-term economic resilience (Dai et al., 2022; King & Levine, 1994; Sarpong et al., 2023). Now, firms are emphasising technology and in-house R&D (Li et al., 2022; Radicic & Balavac, 2019). This approach allows a firm to distinguish itself from competitors, fostering a unique market position (Zhang et al., 2022). Thus, firms are increasingly motivated to prioritise innovation to remain competitive and flourish in the global market (Bodhanwala & Bodhanwala, 2025). As a result, the firm can achieve a greater market share and increased profitability, thereby fulfilling its fundamental commercial objectives (Li et al., 2022; Lu, 2020). R&D intensive firms enjoy higher growth potential and thus are highly recognised by the investors (Hasan et al., 2022; Tsai & Wang, 2005). R&D financing is integral to the innovation process and the overall development of a firm (Zaman & Tanewski, 2024). Deliberate attention must be given to financing costs and funding sources when formulating R&D decisions (Broome et al., 2023), as financing R&D through external sources remains challenging and often expensive due to the substantial capital requirements and the inherent uncertain outcomes (Chiu et al., 2024; Giebel & Kraft, 2024; Kou et al., 2020; Moon, 2022).

Financing is essential for firms as it provides the resources to sustain day-to-day operations, pursue growth opportunities, invest in innovation, and effectively manage cash flow fluctuations (Dash et al., 2023). Since internal funds are often insufficient to meet all financial needs, borrowing becomes critical for accessing additional resources. Borrowing allows firms to utilise external funds without giving up ownership control, offering flexibility in addressing both short-term operational demands and long-term strategic goals (Behera & Sethi, 2024). Adequate financing empowers firms to acquire key assets, expand into new markets, and remain competitive, particularly in dynamic and innovation-driven sectors. Furthermore, timely access to finance supports business continuity, strengthens financial resilience, and enhances the firm's ability to respond to economic challenges (Brown et al., 2012). Without reliable financing options, firms risk missing out on profitable ventures and may face difficulty maintaining stability during uncertain times.

R&D investment is a critical factor shaping firm performance and influencing corporate borrowings. Access to external finance enables firms to engage in capital-intensive and innovation-driven activities, essential for enhancing productivity, competitiveness, and long-term value creation (Hall & Lerner, 2010). For firms with high R&D orientation, borrowings are an important funding source, especially when internal cash flows are insufficient or volatile (Brown et al., 2012). Despite the inherent risks associated with debt, judicious use of leverage can support innovation and operational growth (Murati-Leka & Ramadani, 2025). However, excessive borrowing may impose financial constraints, discouraging long-term R&D commitments due to repayment pressures and lenders' risk aversion (Chava et al., 2017). Therefore, an optimal capital structure that balances debt and innovation is essential for sustaining firm performance and fostering technological advancement.

India's pharmaceutical sector has emerged as a global leader, known for its massive production capacity, cost efficiency, and innovation. As of 2025, the industry is valued at approximately \$66–\$67 billion and is projected to reach between \$88 and \$130 billion by 2030 (Motilal Oswal, 2025). Moreover, it is ranked 3rd globally by volume and 14th by value, and fulfils over 50% of UNICEF's vaccine requirements, provides 50% of the world's vaccines, and supplies 40% of generic drugs in the U.S. and 25% of medicines in the U.K. (GOI, 2025). Additionally, it fulfils nearly 90% of the WHO's requirement for the measles vaccine (Ministry of Chemicals and Fertilizers, 2023; World Health Organisation, 2024). Its contributions are particularly significant in achieving fundamental SDG-3 targets such as universal health coverage, equitable access to essential medicines and vaccines, and the ongoing research and development of effective treatments for both communicable and non-communicable diseases (United Nations, 2015). Pharmaceutical firms play a vital role in promoting SDG-3 by supporting the development and distribution of affordable, safe, effective, and superior medicines and vaccines, especially for the general masses of developing countries (IBEF, 2025).

Therefore, understanding the influence of R&D intensity on corporate borrowings is essential for managers and policymakers seeking to optimise resource allocation and support sustainable business expansion. The firm's successful R&D initiatives drive the development of new products and enhance production efficiency, empowering the firm to enter new markets or reduce the cost of production as corporate borrowings act as a critical driver in shaping firm performance and influencing the intensity of R&D investments. Access to external finance enables firms to engage in capital-intensive and innovation-driven activities, which are critical for enhancing productivity, competitiveness, and long-term value creation (Hall & Lerner, 2010). Thus, firms' R&D investment decisions are intrinsically linked to their corporate borrowing strategies, as access to financing plays a pivotal role in sustaining innovation efforts, particularly in innovation-intensive sectors like the pharmaceutical sector. With the rise of an industrialised and globalised economy, and the growing focus on technology and in-house R&D in developing countries like India, the relationship between corporate borrowings and firms' R&D intensity continues to be a compelling area of inquiry. The rest of the paper is organised as follows: Section 2 deals with literature review, Section 3 encompasses description of Data and methodology, Section 4 focuses on results and discussion, and Section 5 deals with conclusion.

## 2. Review of Literature

R&D investment is one of the critical activities that any business or corporation can use to produce and boost new products, services, and processes to enhance firm value (Gharbi et al., 2014). In the present scenario of rapid economic change, investment in R&D has become indispensable for fostering innovation, driving business growth, and sustainable success (Morina et al., 2025). R&D expenditure is the key factor in predicting firm innovation activities (Jaklic et al., 2014). Moreover, Da Silva et al. (2015) found that R&D is a critical factor toward corporate success, growth, and survival, and is called as a proxy for corporate innovation. In line with this study, Sharma (2012) and Wu et al. (2019) have demonstrated a positive relationship between R&D investment and firm performance. With the growing swiftness of technological change and the distribution of knowledge in most industrial environments, R&D investment has become crucial for prosperity and sustainability (Chun, 1990). Thus, in response to intense competition, firms engage in innovation and product diversification to capture growth prospects, enhance profitability, and outperform their competitors (Farida & Setiawan, 2022). Stakeholders have considered the importance of R&D initiatives (Gao et al., 2017). Thus, firms use R&D investment to respond to stakeholder demands and secure superior outcomes (Han & Manry, 2004). Previous studies have documented the positive influence of R&D investment on firm performance (Hall et al., 2013; Khanna & Sharma, 2018; Kim et al., 2018; Koutroumpis et al., 2020; O'Mahony & Vecchi, 2009; Sharma, 2012; Tsai & Wang, 2005). Daunfeldt & Elert (2013) investigate R&D expenditure from diverse industries; findings reveal a substantial heterogeneity in R&D intensity and innovation persistence among firms. Chung et al. (2019) validate that R&D intensity drives firm growth.

Given the above, assessing the value attributed to R&D as a key resource is increasingly important amid rapidly changing business conditions. R&D intensive policies are initiated through prevailing economic and social structures important for sustainable development (Nair et al., 2020; Zafar et al., 2019). Pioneer study of Solow (1957) documented that technological change is the force behind the productivity growth. While endogenous growth theorists acknowledge its significance, they contend that it arises internally, through purposeful resource investment by profit-oriented firms (Grossman & Helpman, 1991 & 1994). Through dedicated R&D investment, firms not only increase the value embedded in their offerings but also cultivate a culture of agility and continuous advancement. This strategic focus empowers organisations to anticipate and adapt to shifting market dynamics, meet emerging customer needs, and secure a lasting competitive edge. Rather than being a routine expense, R&D catalyses long-term profitability, industry leadership, and resilience in global competition (OECD, 2023).

Over the past few years, corporate R&D has garnered significant scholarly attention. Numerous studies have explored its relationship with various firm specific factors, including corporate governance and managerial discretion (Dong & Gou, 2010), government subsidies (Lee & Cin, 2010), firm size and intangible resources (Lai et al., 2015), family ownership structures (Sciascia et al., 2015), foreign ownership (Anwar & Sun, 2014), shareholder protection laws (Li et al., 2024), property rights (Lin et al., 2009), managerial incentives and CEO characteristics (Chen, 2013), internationalisation (Filatotchev & Piesse, 2009; Hsu et al., 2015) foreign direct investment (Anwar, 2013; Usman et al., 2022), and corporate social responsibility (Jose et al., 2018).

Firms in technology-intensive sectors such as electronics, automotive, and innovative-intensive sectors such as pharmaceuticals, biotechnology, and computer manufacturing often experience a significant increase in sales volume after successfully commercialising innovations (Nieto Cubero et al., 2021). Similarly, the prior study of Demirel & Mazzucato (2012) demonstrated that R&D fosters growth in the pharmaceutical sector, primarily by creating high entry barriers that limit competition. Implementing the TRIPS Agreement in 2005 introduced substantial reforms to the intellectual property regime, particularly in intellectual property rights (Tyagi, 2024). R&D efforts by Indian pharmaceutical firms are primarily focused on developing processes and generic versions of high-potential drugs from developed countries with soon-to-expire patents (Sahasranamam et al., 2019). Remarkably, A higher rate of return on R&D investments is observed in emerging economies like India compared to developed countries (Shivdas & Ray, 2021). The Patent (Amendment) Act of 2005 catalysed increased investment in R&D and new drug development, compelling firms to improve efficiency and maintain growth within a highly price-sensitive environment, particularly following the implementation of the TRIPS-compliant product patent regime (Mahajan, 2019; Mahajan et al., 2015). In light of these developments, the emphasis on R&D investment is crucial for sustainable progress. In light of the above context, this paper aims to investigate the influence of R&D intensity on corporate borrowings of Indian pharmaceutical firms during 2015–2024. This study considers the impact of R&D intensity of pharmaceutical firms along with the additional control variables such as sales growth, firm age, cash flow, dividend payment, firm size, EPS, and market capitalisation.

## 3. Research Methodology

### 3.1. Data and methodology

Firms' data on the Indian Pharmaceutical sector are collected from the Prowess database provided by the Centre for Monitoring Indian Economy (CMIE) for 10 years from 2015 to 2024. The procedures for sample selection are as follows. Data on 149 Indian Pharmaceutical firms available on the database are collected, of which 52 firms with missing data are excluded, resulting in a final sample of 97 firms with 970 firm-year observations.

This study conducts an empirical investigation using panel data from Indian pharmaceutical firms. To analyse and interpret the data, the study begins with the application of summary statistics to provide an overview of the variables. Subsequently, correlation analysis is employed to explore the nature and strength of the associations between the variables. Finally, the study applies the ordinary least squares (OLS) regression technique to assess the impact of firms' R&D intensity on borrowings. Variables, along with their definitions, are outlined in Table 1.

### 3.2. Empirical Model

This study intends to investigate the influence of R&D intensity on corporate borrowings of the sample firms. To assess the connection between R&D intensity and corporate borrowings, estimate the baseline equation using the OLS regression. The regression model is as follows:

$$CB_{it}=\alpha_0+\beta_1 RDI_{it}+\beta_2 SG_{it}+\beta_3 FA_{it}+\beta_4 CF_{it}+\beta_5 DP_{it}+\beta_6 FS_{it}+\beta_7 EPS_{it}+\beta_8 MC_{it}+\varepsilon \qquad \text{---------------} \ (1)$$

Regarding the dependent variable, this study uses corporate borrowings, defined as the ratio of the sum of short-term and long-term borrowings to total assets (Berg et al., 2021). The independent variable is R&D intensity, a proxy for the level of R&D investments, measured as the ratio of R&D expenditures to total sales in the same year (Wu et al., 2019). Based on Chung et al. (2019), Mahajan (2019), Sharma (2012), and Shivdas & Ray (2021), this study has the following control variables. Specifically, this study controls the sales growth, firm age, cash flow, dividend payment, firm size, EPS, and market capitalisation. Table 1 presents the description of the variables used in the analysis.

**Table 1: Variable Description**

| Variable | Abbreviation | Description |
|---|---|---|
| **Corporate Borrowing** | CB | The ratio of the sum of short-term and long-term borrowings to total assets. |
| **R&D Intensity** | RDI | The ratio of R&D expenditures to the total sales in the same year. |
| **Sales Growth** | SG | The difference between sales in period t and period t-1 as a percentage of total assets. |
| **Firm Age** | FA | Number of years since incorporation. |
| **Cash Flow** | CF | The ratio of cash flow from operating, financing, and investing activities to total assets. |
| **Dividend Paid** | DP | The ratio of dividend payment to total assets. |
| **Firm Size** | FS | Natural logarithm of total assets. |
| **Earnings Per Share** | EPS | The ratio of a firm's net profit after tax to the number of outstanding equity shares. |
| **Market Capitalisation** | MC | The product of a company's share price and the total number of its outstanding equity shares. |

Source: Authors' collection.

## 4. Results and Discussion

### 4.1. Summary Statistics

Table 2 presents the descriptive statistics of the variables employed in this study. The average borrowing level among the Indian pharmaceutical firms is approximately 46.9% of total assets, indicating a moderate reliance on external financing. However, the wide range from 5.7% to 381% suggests significant heterogeneity in capital structure, with some firms operating conservatively while others exhibit a higher external financing. With respect to R&D intensity, the data show a mean of 16.9%, but a much lower median of 1.6%, coupled with an exceptionally high standard deviation. This reveals a strongly right-skewed distribution, where a few firms invest heavily in R&D, while the majority allocate relatively minimal resources. This disparity underscores the uneven commitment to innovation within the pharmaceutical firms. Cash flow includes negative values and reflects the presence of firms facing liquidity constraints. Similarly, the dividend paid shows a low mean, with minimum values, suggesting that some firms have reduced or suspended dividends due to earnings volatility or strategic reinvestment decisions. The wide dispersion points to a divergence in dividend policies across firms in the sector. Firm size is fairly consistent across firms, though a few extreme values indicate the presence of very large and very small firms. Regarding Earnings Per Share (EPS), the high standard deviation and the gap between the mean and median reflect substantial variation in firm profitability. Market capitalisation shows skewness, which shows the disparity in investor valuation within the sector.

**Table 2: Summary statistics**

| Variable | Mean | Median | S.D. | Min | Max |
|---|---|---|---|---|---|
| **Borrowing** | 0.469 | 0.393 | 0.358 | 0.057 | 3.810 |
| **RD Intensity** | 0.169 | 0.016 | 2.740 | 0.000 | 82.300 |
| **Firm Age** | 36.200 | 33.000 | 18.600 | 0.000 | 88.000 |
| **Cash Flow** | 0.004 | 0.001 | 0.056 | -0.484 | 0.493 |
| **Dividend Paid** | 0.010 | 0.002 | 0.044 | -0.522 | 0.453 |
| **Firm Size** | 6.430 | 6.390 | 1.980 | 2.070 | 10.700 |
| **EPS** | 22.000 | 9.740 | 50.400 | -379.000 | 662.000 |
| **Market Capitalisation** | 78.100 | 1.440 | 2.230 | 0.000 | 6.520 |

Source: Authors' calculation.

## 4.2.Correlation Matrix

Table 3 presents Karl Pearson's correlation coefficient among the study variables, offering the linear associations between corporate borrowings, R&D intensity, and other control variables. The correlation between corporate borrowings and R&D intensity is negative but negligible (r = -0.036), suggesting that the extent of R&D investment has minimal association with a firm's reliance on external financing in the Indian pharmaceutical sector. Borrowings exhibit a modest negative correlation with firm size (r = -0.223) and EPS (r = -0.213), indicating that larger and more profitable firms tend to rely less on external funding, due to their access to retained earnings or alternative funding sources. R&D intensity, on the other hand, shows very weak correlations with all other variables, with the highest being a positive but minimal relationship with firm size (r = 0.047), implying that larger firms marginally allocate more resources toward innovation activities. Firm age exhibits weak positive correlations with firm size (r = 0.100) and EPS (r = 0.196), suggesting that older firms enjoy some advantages in terms of scale and profitability. Dividend payments are positively associated with firm size (r = 0.124) and EPS (r = 0.133), indicating that larger and more profitable firms are more likely to distribute dividends. Notably, market capitalisation demonstrates a moderate negative correlation with firm size (r = -0.252), which may point to valuation inefficiencies or structural irregularities within the sector. Overall, the low correlation coefficients suggest no multicollinearity issue among the independent variables, which supports the robustness of subsequent regression analyses aimed at identifying the influence of R&D intensity on corporate borrowings of Indian pharmaceutical firms.

**Table 3: Correlation matrix**

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| **1. Borrowing** | 1 | | | | | | | | |
| **2. R&D Intensity** | -0.036 | 1 | | | | | | | |
| **3. Sales Growth** | 0.007 | -0.007 | 1 | | | | | | |
| **4. Firm Age** | 0.054 | -0.009 | -0.017 | 1 | | | | | |
| **5. Cash Flow** | -0.018 | -0.050 | 0.006 | -0.015 | 1 | | | | |
| **6. Dividend Paid** | -0.052 | -0.035 | -0.012 | 0.043 | -0.029 | 1 | | | |
| **7. Firm Size** | -0.223 | 0.047 | -0.067 | 0.100 | -0.033 | 0.124 | 1 | | |
| **8. EPS** | -0.213 | -0.008 | -0.046 | 0.196 | 0.005 | 0.133 | 0.304 | 1 | |
| **9. Market Capitalisation** | 0.021 | -0.002 | 0.063 | -0.003 | -0.003 | -0.008 | -0.252 | -0.015 | 1 |

Source: Authors' calculation.

## 4.3.Regression Results

This study adopts OLS regression approach, consistent with the methodology employed by Lechner et al. (2015), as it provides reliable and interpretable estimates. Table 4 depicts the results of the OLS regression analysis employed to examine the influence of firm-specific variables on corporate borrowings among Indian pharmaceutical firms. The regression results indicate that R&D intensity has a negative impact on corporate borrowings (coefficient = −0.0034, $p < 0.0001$). This suggests that firms with higher investment in R&D (R&D intensive) are less inclined to finance their operations through debt, due to the intangible and uncertain nature of R&D activities, which limits their suitability as collateral and makes lenders more cautious (Behera & Sethi, 2024). This finding aligns with existing theoretical expectations that R&D-intensive firms prefer internal financing or equity over debt to avoid financial distress and maintain operational flexibility (Sahoo et al., 2023). Firm size also negatively influences borrowings (coefficient = −0.0329) and is significant at the 5% level. This indicates that larger firms are likely to rely less on debt, due to better internal cash generation or greater access to non-debt sources of capital (Sethi & Swain, 2019b). Similarly, cash flow shows a significant negative effect, supporting the pecking order theory, which posits that firms with strong internal financial resources prefer to use them over external financing (Dash et al., 2023; Dash & Sethi, 2024). The coefficients for firm age, PAT, sales growth, and market capitalisation are statistically insignificant, suggesting that these variables don't substantially influence the borrowing behaviour of indian pharmaceutical firms. These results imply that profitability, market performance, or firm maturity do not directly determine debt usage in Indian pharmaceutical firms. Finally, the OLS regression results underscore the significance of R&D intensity, firm size, and internal cash flow in influencing borrowing decisions, while highlighting the limited role of traditional indicators such as firm age and profitability in the Indian pharmaceutical context.

**Table 4: Regression analysis**

| Variables | Coefficient | t-ratio | p-value |
|---|---|---|---|
| **R&D Intensity** | −0.0034*** | −4.848 | <0.001 |
| **Firm Size** | −0.0329* | −1.985 | 0.050 |
| **Firm Age** | 0.0016 | 0.865 | 0.391 |
| **PAT** | −0.3955 | −1.383 | 0.169 |
| **Cash Flow** | −0.2961** | −2.254 | 0.026 |
| **Sales Growth** | −1.7710 | −1.147 | 0.254 |
| **Market Capitalisation** | −4.5312 | −1.144 | 0.256 |
| **Intercept** | 0.6465*** | 4.851 | <0.001 |
| **Adjusted R-squared** | 0.248 | | |
| **F(7, 95)** | 52.206 | | |
| **P-value(F)** | 8.000 | | |
| **Observation** | 970 | | |

Note: ***, **, and * indicate significant level at 1%, 5% and 10% respectively.
Source: Authors' calculation.

The empirical findings from both the correlation matrix and OLS regression provide valuable insights into the borrowing behaviour of Indian pharmaceutical firms concerning their R&D intensity. The correlation results reveal a negative association between R&D intensity and corporate borrowings, while the OLS regression confirms a statistically significant and negative relationship between the two. This finding suggests that firms emphasising R&D tend to rely less on debt financing. The result aligns with the theoretical premise that R&D investments, being intangible, risky, and long-term in nature, offer limited collateral value, thereby discouraging debt-based financing (Hall, 2002; Hall & Lerner, 2010). Similar evidence is presented by Brown et al. (2012), and Sahoo et al. (2023) who argue that innovative firms often face external financing constraints and thus prefer internal finacing to support R&D. The negative and significant impact of firm size and cash flow on borrowings further reinforces the applicability of the pecking order theory (Sethi et al., 2021), which posits that firms prefer internal sources of finance over external debt to avoid disclosure costs and financial distress (Myers & Majiuf, 1984). Due to economies of scale and better market access, larger firms may generate sufficient internal funds to finance R&D without debt (Zou & Ghauri, 2008). The significance of cash flow as a negative determinant of borrowings is also in line with the findings of Bhagat & Welch (1995), who observed that firms with strong internal cash flows are less dependent on external financing. Conversely, variables such as firm age, profit after tax, sales growth, and market capitalisation do not show significant associations with corporate borrowings, either in the correlation or regression models. This is consistent with findings of Czarnitzki & Hottenrott (2011 & 2012), who noted that traditional indicators of firm performance are not always reliable predictors of debt usage in innovation-intensive industries. These findings contribute to the growing body of literature on financing decisions in R&D driven sectors by emphasising the unique financing preferences of pharmaceutical firms in emerging markets like India. The observed patterns indicate that innovation-oriented firms strategically avoid debt, consistent with prior international studies. Aghion et al. (2004) highlighted the importance of strengthening internal resources or alternative financing mechanisms to sustain long-term innovation.

## 5. Conclusion

This study investigates the relationship between corporate borrowings and R&D intensity of Indian pharmaceutical firms, offering valuable insights into the financing behaviour of innovation-driven firms in an emerging economy like India. The findings of empirical analysis suggest that R&D

intensive pharmaceutical firms tend to rely less on debt financing, due to the intangible, risky, and high-cost non-collateralisable nature of R&D investments. The results reinforce the theoretical arguments of the pecking order theory and support existing literature (Brown et al., 2012; Hall, 2002; Myers & Majiuf, 1984; Sethi et al., 2021; Sethi & Swain, 2019), indicating a preference among R&D-intensive firms for internal financing mechanisms. Additional evidence showing negative impacts of firm size and cash flow on borrowings further underscores this financing hierarchy in determining borrowing behaviour, aligning with findings from studies on innovation-intensive sectors (Czarnitzki & Hottenrott, 2011). These findings contribute to the broader understanding of financing strategies in innovation-intensive sectors by highlighting the distinctive financial dynamics of Indian pharmaceutical firms.

As this study is confined to Indian pharmaceutical firms, future research can expand the scope by incorporating firms from all the manufacturing firms in India. Such an extension will allow for a more comprehensive and nuanced understanding of how R&D intensity influences corporate borrowings across diverse industries.

The study provides important managerial implications for Indian pharmaceutical firms. The negative association suggests that managers should prioritise internal financing over external financing to support innovation, given the intangible and high-risk nature of R&D activities. Strong internal cash flows and retained earnings become essential for sustaining long-term innovation strategies. In line with the pecking order theory, managers are encouraged to adopt financial practices that enhance liquidity and minimise reliance on debt. This calls for a more nuanced approach to financing planning, where innovation goals are integrated into financial decision-making. Moreover, firms should explore alternative financing sources such as government grants, venture capital, or strategic alliances to mitigate financing constraints and strengthen their innovation capacity without incurring financial risk.

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Promoting Research

# Exchange Rates and GDP: A Bibliometric and Scientific Mapping Study

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**Abstract:** This study presents a bibliometric and scientific mapping analysis of research on the nexus between exchange rates and Gross Domestic Product (GDP) from 1968 to 2023. Based on 1,799 publications retrieved from Scopus and Web of Science using a structured keyword string, the data were analyzed through R Studio Biblioshiny to examine intellectual foundations, thematic evolution, and collaboration patterns. Results show a significant rise in publications after the 1990s, with leading outlets including Economic Modelling, Applied Economics, and the Journal of International Money and Finance. Influential institutions such as the National Bureau of Economic Research (NBER) and the International Monetary Fund (IMF) dominate contributions, while key scholars include Hsing Y and Aizenman J. Co-citation networks reveal two intellectual pillars: econometric methodology (Engle, Johansen, Blundell, Granger) and macroeconomic-policy debates (Rodrik, Dollar, Edwards). Thematic mapping identifies core areas in exchange rates, inflation, monetary policy, and growth, along with emerging themes in exchange rate regimes, forecasting, reserves, and Sub-Saharan African studies. Thematic evolution traces a shift from purchasing power parity and Dutch disease to capital flows, debt, and COVID-19 shocks. The study consolidates fragmented literature and identifies gaps in forecasting, debt sustainability, and global shock transmission.

## 1. Introduction

Understanding the relationship between exchange rates and economic growth has long been a central concern in international economics. Exchange rate fluctuations shape GDP growth, trade balances, and sectoral performance, with varying effects across countries and time periods. For instance, exchange rate misalignments have been linked to growth contractions through chronic overvaluation. (Ndhlela, 2012), while currency depreciation has been shown to boost trade balances and manufacturing output in the short run (Choi, 2017) (Babubudjnauth, 2021). Conversely, appreciation and volatility often undermine exports (Jaussaud & Rey, 2012) and can distort GDP measurement when expressed in foreign currency terms (Zhao et al., 2020). These mixed findings reflect the complex and context-dependent nature of the exchange rate–growth nexus.

Recent literature also highlights the interplay between exchange rates and broader macroeconomic indicators. Factors such as inflation, interest rate differentials, trade openness, and capital flows significantly shape currency dynamics (Kia, 2013) (Khan et al., 2019). Evidence suggests that exchange rate returns often embed signals about future GDP growth and inflation (Lima & Terra, 2021) (Jaworski, 2021), while announcement shocks, such as GDP releases, trigger lasting effects in currency and futures markets (Chen & Gau, 2022). These findings underscore the exchange rate's dual role as both a driver and a reflection of macroeconomic performance.

At the same time, global developments have amplified the urgency of understanding these dynamics. The COVID-19 pandemic, trade wars, financial crises, and recent surges in inflation have intensified currency volatility worldwide, reshaping the stability of growth trajectories and the competitiveness of nations. This evolving landscape makes it essential to systematically map the intellectual progress of this field.

Yet, despite extensive research, the literature remains fragmented—spanning themes from purchasing power parity and Dutch disease in earlier decades to more recent emphases on capital flows, exchange rate pass-through, and unemployment. What is missing is an integrated overview that identifies how research in this area has evolved, where the scholarly focus lies today, and which gaps remain. Bibliometric analysis and scientific mapping provide powerful tools to fill this void by combining quantitative insights—such as publication trends, leading authors, and institutional contributions—with qualitative dimensions like co-citation networks, thematic structures, and the evolution of research fronts.

Accordingly, this study applies bibliometric and scientific mapping techniques to analyze the exchange rate–growth literature. The objectives are to: (i) assess the volume and trajectory of publications, (ii) identify influential sources, researchers, institutions, and countries, and (iii) map the intellectual and thematic structure of the field. By doing so, this study contributes both a comprehensive synthesis of past scholarship and a roadmap for future research in an area that remains vital to global economic stability.

## 2. Review of Literature

The relationship between GDP and exchange rate dynamics has been widely investigated in the literature, with mixed and context-specific findings. Several studies emphasize that fluctuations in the exchange rate significantly affect GDP growth, with a rising exchange rate often associated with declining GDP performance (Yang et al., 2013) (López et al., 2011) (Hsing & Hsieh, 2009). Exchange rate movements also shape trade openness, as measured through the trade-to-GDP ratio, which has been shown to be significantly influenced by the real effective exchange rate (REER) (Bleaney & Tian, 2023). At the micro level, GDP per capita captures the relationship between exchange rate volatility and exports. For instance, (Hsu & Chiang, 2011)found that volatility reduces U.S. exports to high-income partner countries, while simultaneously encouraging exports to low-income partners. Similarly, undervaluation of the domestic currency enhances export competitiveness, thereby fostering national economic growth (Zhu et al., 2022). However, contradictory evidence exists, as (Fincke & Greiner, 2015) reported no significant impact of exchange rate and trade balance on economic growth.

The exchange rate itself is broadly defined as the value of one currency in terms of another, capturing appreciation and depreciation trends. Its behavior is strongly linked to macroeconomic fundamentals. (Khan et al., 2019) highlighted the positive role of GDP and trade balance in influencing exchange rates and stressed the importance of maintaining a stable and less volatile exchange rate through appropriate monetary and fiscal policies. Further, GDP impacts exchange rate movements both in the short and long run (Eslamloueyan & Kia, 2015), while interest rate differentials alongside GDP are important determinants of co-movements in foreign exchange markets across emerging economies (Djemo & Eita, 2024).

## 3. Research Methodology

The growing body of literature and rapidly increasing research activities have resulted in a vast amount of available studies for researchers to conduct literature reviews and identify research gaps. However, this abundance of literature creates difficulties in identifying the most relevant studies. Over time, new and fresh topics have also emerged, contributing to the advancement of existing knowledge and the development of the world. This research has been undertaken to identify and quantify the work conducted in this area during 1968-2023. To achieve the study objective, the bibliometric analysis technique, along with scientific mapping, has been employed.

## 3.1. Data

Data forms the base for conducting research in any of the areas and fields. Data regarding this bibliometric analysis has been collected from the two leading indexing and abstracting databases at the global level, Scopus and Web of Science. The keyword string used on both platforms is as follows:

(“GDP” OR “Gross Domestic Product”) AND (“forex rate” OR “Foreign exchange rate” OR “FX rate” OR “currency exchange rate” OR “exchange rate”).

| Search string | Scopus | Web of Science |
|---|---|---|
| "GDP" OR "Gross Domestic Product" AND "forex rate" OR "Foreign exchange rate" OR "FX rate" OR " Currency Exchange rate" OR "Exchange rate" | Search field: Article title, Abstract, and Keywords **(Results: 2563)**<br><br>Category: Economics, Econometrics and Finance; Social Sciences; Business, Management and Accounting **(Results: 2079)**<br><br>Document type: Articles, Book Chapter, Proceeding Paper **(Results: 1790)**<br>Publication stage: **(Results: 1754)**<br>Language: English **(Results: 1650)** | Search field: Topic<br>Years: 1995-2023<br>**(Results: 962)**<br>Document type: Articles<br>**(Results: 946)**<br>Category: Economics; Business Finance; Business management; International relations<br>**(Results: 642)** |

**Figure 1: Workflow of study**

Using the above-mentioned keyword string in Scopus provided the researcher with 2563 results, and to make these results suitable and relevant for this study, various category filters, document type filters, publication stage, and language filters were used, which reduced the number of articles to 1650. At the time of applying these filters, articles in Economics, Econometrics and Finance, Social Sciences, and Business, Management and Accounting categories were included only, while the rest of the category items were excluded. The application of the research article filter resulted in the inclusion of different types of documents, such as books, proceedings papers, early access articles, and research articles. These filters resulted in the exclusion of 913 articles from Scopus.

In the Web of Science datafile, the search string provided 962 articles, which were included based on the article category, conference proceedings, book chapters, and early access**.** In the Web of Science category filter, articles belonging to Economics, Business Finance, Business Management, and International Relations were included, and the rest of the categories were excluded. The last filter was the language filter, where articles in the English language were included, while the rest of the articles were excluded. These filters resulted in the availability of the most relevant literature in the field of exchange rate and Gross Domestic Product, setting a good study base for conducting this research. These exclusion criteria brought the number of articles to be included in this research to 642 documents from Web of Science.

The list of Scopus data and Web of Science data was merged using R Studio, which found 468 duplicate documents in both files. The software also removed some other items. As a final result, 1808 documents were available. These results were again scrutinised for any missing entries or inconsistencies, and 9 entries with missing authors’ names were removed. The final result was 1799 articles. The bibliometric analysis, along with scientific mapping of the available data of 1799 articles, was conducted to draw some interesting and meaningful conclusions.

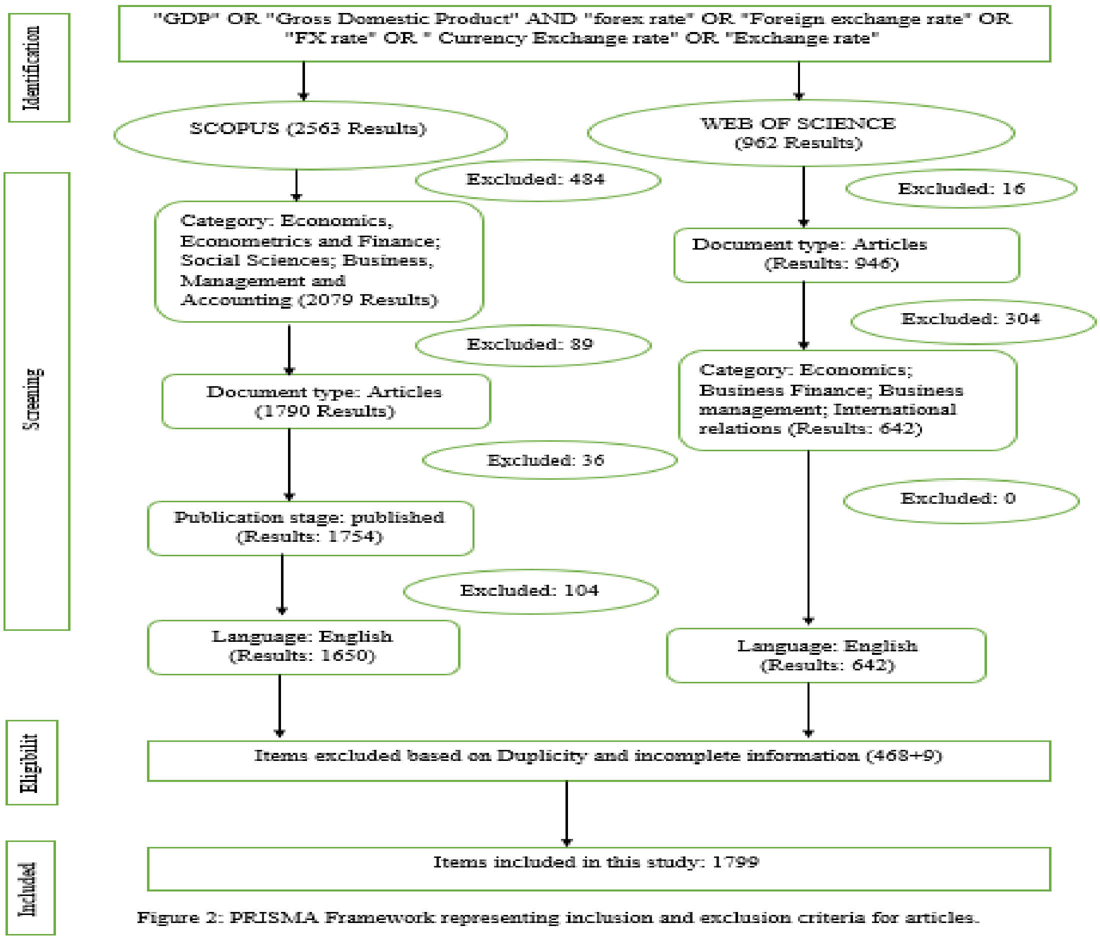

Figure 2: PRISMA Framework representing inclusion and exclusion criteria for articles.

## 4. Results and Discussion

The collected data were analysed using R Studio Biblioshiny. Using R Studio, both bibliometric and scientific analyses were performed on the data. The analysis conducted through the software and its interpretation are provided in the upcoming sections of this article. Bibliometric analysis is concerned with the quantitative examination of major information such as the number of articles available, their annual growth rate, top authors, top sources, leading institutions, and countries in the research area. Scientific mapping is concerned with formulating intellectual insights from the available data to create the co-word network, thematic analysis, country and institutional collaboration network, and co-citation network of authors and journals.

## Bibliometric Analysis

This section will contain the quantitative analysis of the available literature in this area of research. It will include a summary statement, briefing the details of the available literature in terms of their count, sources, authors, and keywords. It will also provide details regarding the most prominent authors, sources, institutions, and countries based on their number of publications, total citations, h-index, and other relevant metrics.

**Table 1: Summary table**

| Description | Results |
|---|---|
| MAIN INFORMATION ABOUT DATA | |
| Timeline | 1968:2023 |
| Sources (Journals, Books, etc) | 630 |
| Documents included | 1799 |
| Annual Growth Rate % | 9.11 |

| **Description** | **Results** |
|---|---|
| Document Average Age | 10.3 |
| Average citations per doc | 13.38 |
| References | 20675 |
| DOCUMENT CONTENTS | |
| Keywords Plus (ID) | 1708 |
| Author's Keywords (DE) | 3600 |
| AUTHORS | |
| Total Authors | 3392 |
| Authors of single-authored docs | 424 |
| AUTHORS COLLABORATION | |
| Single-authored documents | 486 |
| Co-Authors per Document | 2.25 |
| International co-authorships % | 10.78 |
| DOCUMENT TYPES | |
| Article | 1753 |
| article; book chapter | 1 |
| article; early access | 20 |
| article; proceedings paper | 25 |

Source: Author's Compilation.

Table 1 provides some basic details about the list of articles downloaded from Scopus and Web of Science. It shows that the range of articles spans from 1968 to 2023. The articles obtained from both databases total 1,799 from 630 sources, which indicates that, on average, each source has published 2.85 articles. The annual growth rate of articles in this field is 9.11, with the average age of documents being 10.3 years. The average citations per document are 13.38, and the reference lists of the documents are very large, containing 20,675 references. The authors' keywords identified were 3,600, while the keyword plus terms were 1,708. Out of 1,799 documents, 486 are single-authored works written by 424 authors.

## 4.1. Annual Scientific Production

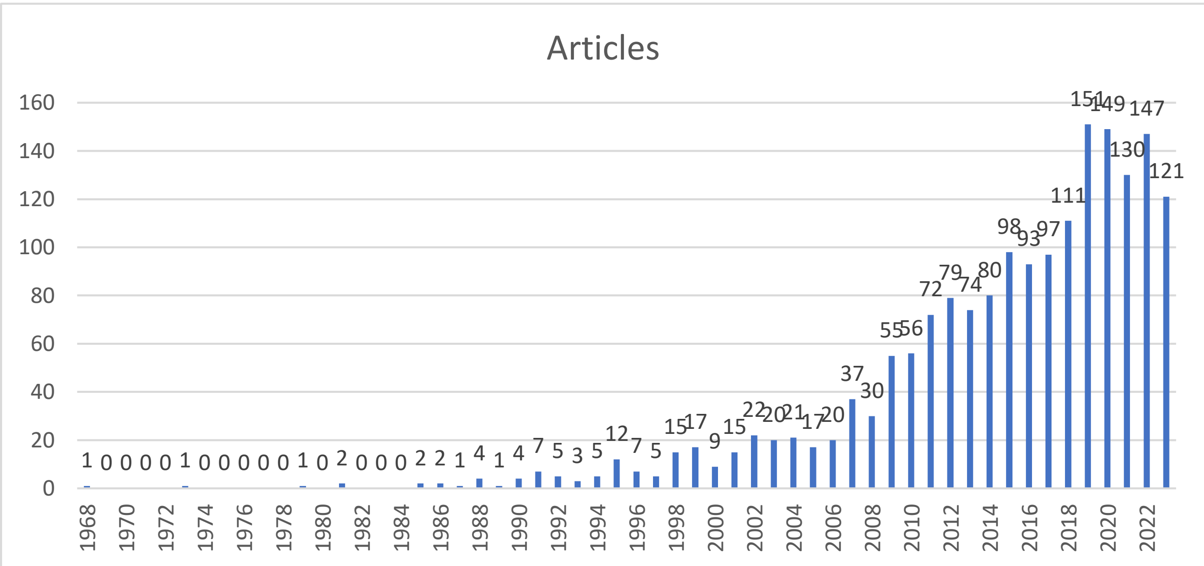


**Figure 3: Annual article production**

Annual article production during 1968-2023 is represented in the form of a chart in Figure 3. This chart clearly shows an increasing trend in the publication of documents. In the initial years, publications in this field were very few; in some years, there were even 0 publications related to this field. However, after 1990, this research topic took off, and the number of publications increased, reaching the benchmark of 151 publications in 2019, 149 publications in 2020, and 147 in 2022. This increasing number of publications over the past 10 years showcases the growing interest of researchers in this area. This trend could be associated with the collapse of the Bretton Woods System, after which countries gradually started adopting a flexible exchange rate. Along with this, the increasing trade liberalization measures adopted also had a significant impact on the exchange rate, as it could affect the competitiveness of products; therefore, the exchange rate was studied more during that time.

## 4.2.Average Annual Citations Per Article

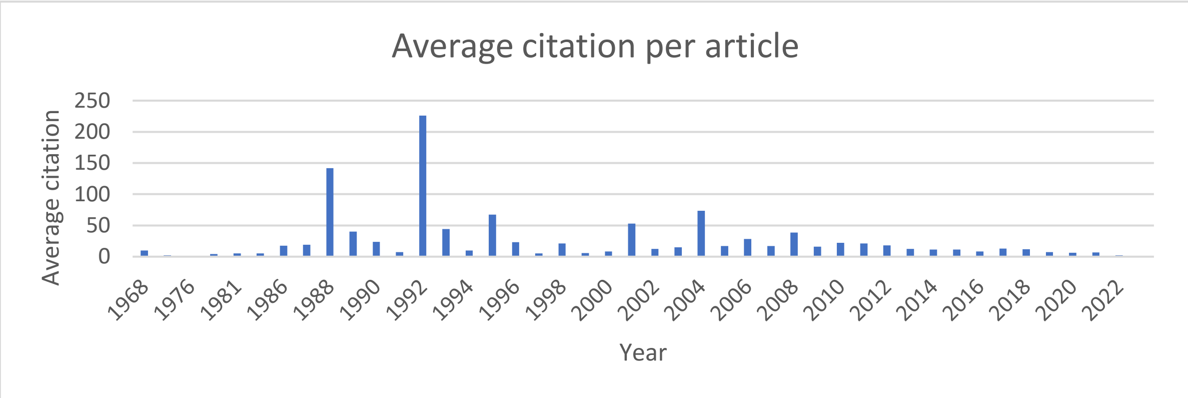


**Figure 4: Average citation per article**

Figure 3 showcases the annual production of articles, and Figure 4 represents the share of each article in the citations received during a particular year. The average citation for the year 1992 was 226.2, with 5 publications during that year. This means that the total citations received in 1992 were 1,130, which were distributed among the 5 articles using the averaging method, so each article received 226.2 citations on average. In 1988, the average citation per article was 141.75, followed by 73.48 citations in 2004.

## 4.3.Three-field Plot

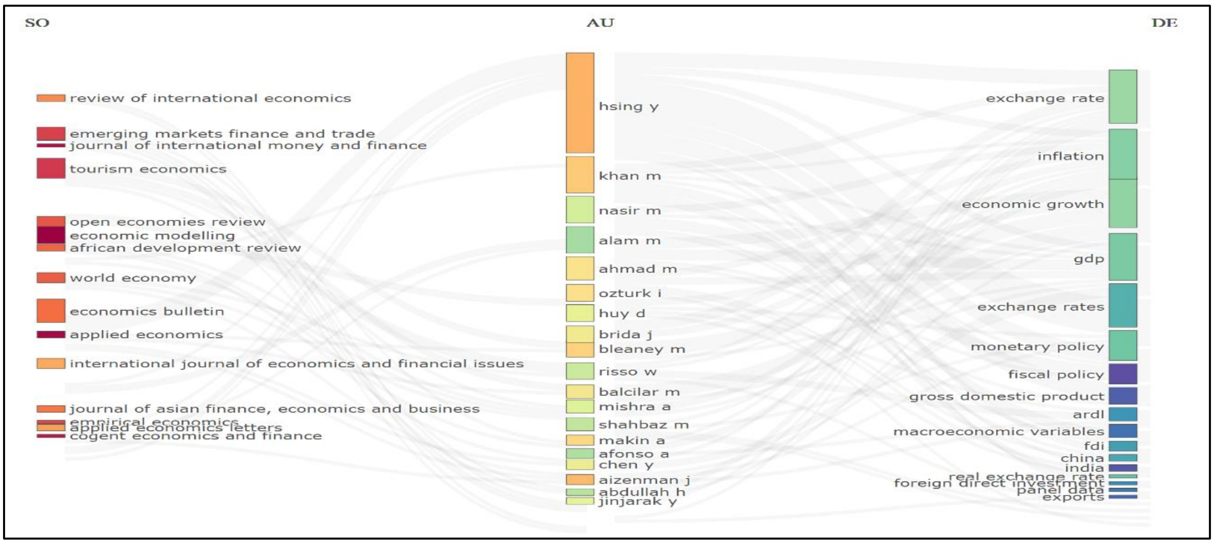


**Figure 5: Three-field plots**

The three-field plot above depicts three different fields related to articles in one figure. In Figure 5, So stands for Source (Journal), AU stands for Author, and DE stands for Author Keywords. These three different fields are presented in a single chart to illustrate their relationships. The most important author, as per this chart, is Hsing Y, who has published work in the *International Journal of Economics and Business Research, International Journal of Economics and Financial Issues, Journal of Asian Finance, Economics and Business, Applied Economics Letters,* and *Economics Bulletin,* using the keywords inflation, GDP, exchange rates, monetary policy, and fiscal policy. Khan M has also worked on the keywords exchange rate, inflation, GDP, fiscal policy, monetary policy, and others. Hence, this plot highlights the authors who have worked on similar topics and published their papers in the sources depicted above.

## 4.4. Most Prolific Journal

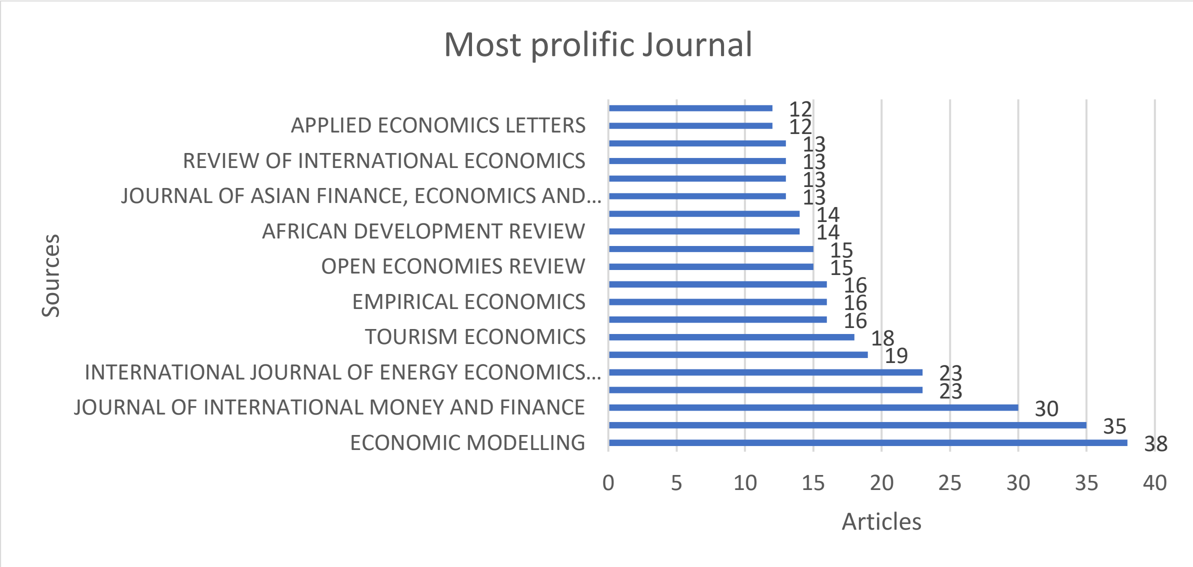


**Figure 6: Most prolific Journal**

The most prolific Journals having a higher number of publications in the field of exchange rate and Gross Domestic Product have been depicted in Figure 6. It shows that the "Economic Modelling" contributing 2.11% in this area with 38 documents published on this topic, and these are covering vast areas such as determinants of "FDI (Foreign Direct Investment)", Marshal-Lerner Condition and export import flow, how the growth of China and US affects small economies exporting commodity, floating exchange rate regime and their optimal Ness, exchange rate movement, and macroeconomic volatility. The next journal is "Applied Economics", having 35 publications and securing 1.94% area in this field, covering the areas of exchange rate volatility, exchange rate and foreign GDP elasticities, interest rate as driving force for inflation and gross domestic product, fiscal and current account imbalances, trade liberalisation and export response. The "Journal of International Money and Finance" has 30 publications covering 1.66% share and contributing to exchange rate dynamics, exchange rate misalignment and its impact on GDP growth, macroeconomic impact of exchange rate regimes, monetary policy impact on exchange rate, GDP growth and currency valuation and so on. The top 20 sources have been depicted here, which have covered 368 documents out of 1799 (20.45%).

## 4.5.Most Impactful Journals

**Table 2: Most Impactful Journals**

| Journals | h-index | g-index | m-index | TC | NP |
|---|---|---|---|---|---|
| Journal of International Economics | 14 | 19 | 0.518 | 1103 | 19 |
| Journal of International Money and Finance | 14 | 24 | 0.666 | 581 | 30 |
| Tourism Economics | 13 | 18 | 0.565 | 1447 | 18 |

| Journals | h-index | g-index | m-index | TC | NP |
|---|---|---|---|---|---|
| Economic Modelling | 12 | 24 | 0.4 | 617 | 38 |
| Applied Economics | 11 | 18 | 0.354 | 365 | 35 |
| World Development | 9 | 13 | 0.225 | 313 | 13 |
| African Development Review | 8 | 14 | 0.228 | 227 | 14 |
| Energy Economics | 8 | 9 | 0.32 | 215 | 9 |
| International Journal of Energy Economics and Policy | 8 | 10 | 0.727 | 136 | 23 |
| Journal of Asian Economics | 8 | 12 | 0.333 | 219 | 12 |
| World Economy | 8 | 11 | 0.296 | 143 | 15 |
| Emerging Markets Finance and Trade | 7 | 14 | 0.318 | 201 | 16 |
| Journal of Policy Modeling | 7 | 12 | 0.269 | 196 | 12 |
| Review of Income and Wealth | 7 | 13 | 0.122 | 680 | 13 |
| Sustainability (Switzerland) | 7 | 10 | 1 | 120 | 16 |
| Cogent Economics and Finance | 6 | 12 | 0.666 | 166 | 23 |
| Empirical Economics | 6 | 10 | 0.428 | 104 | 16 |
| Energy Policy | 6 | 9 | 0.4 | 416 | 9 |
| International Journal of Economics and Financial Issues | 6 | 10 | 0.428 | 120 | 12 |
| International Research Journal of Finance and Economics | 6 | 11 | 0.375 | 136 | 11 |

Source: Author's compilation.

Table 2 provides a list of the most impactful sources, identified based on their h-index. Along with the h-index, other measures of impact, such as the g-index, m-index, total citations, and the number of publications, are also presented in this table. The h-index is used as the major indicator, based on which these sources are arranged in descending order, making the *Journal of International Economics* the most impactful journal, followed by the *Journal of International Money and Finance.* The *Journal of International Economics* has 19 publications and an h-index of 14, which shows that out of 19 articles from this source, 14 articles have received at least 14 citations. Out of 30 publications in the *Journal of International Money and Finance,* 14 articles have received at least 14 citations. The h-index of *Tourism Economics* is 13, based on 18 publications. *Economic Modelling* and *Applied Economics* rank first and second in terms of the number of publications, but their impact is not as strong as other sources, with 18, 19, and 30 articles, respectively.

## 4.6. Most Relevant Authors

**Table 3: Most relevant authors**

| Authors | Articles | h_index | g_index | m_index | TC |
|---|---|---|---|---|---|
| Hsing Y. | 33 | 6 | 11 | 0.285 | 141 |
| Aizenman J. | 9 | 8 | 9 | 0.571 | 165 |
| Khan M. | 8 | 4 | 7 | 0.571 | 56 |
| Bleaney M. | 6 | 5 | 6 | 0.192 | 70 |
| Makin A. | 6 | 1 | 1 | 0.041 | 4 |
| Ozturk I. | 6 | 4 | 6 | 0.235 | 71 |
| Ahmad M. | 5 | 2 | 4 | 0.076 | 17 |
| Balcilar M. | 5 | 5 | 5 | 0.357 | 200 |
| Brida J. | 5 | 5 | 5 | 0.294 | 450 |
| Chen Y. | 5 | 2 | 3 | 0.285 | 9 |
| Huy D. | 5 | 4 | 5 | 0.666 | 53 |
| Jinjarak Y. | 5 | 4 | 5 | 0.363 | 42 |

| Authors | Articles | h_index | g_index | m_index | TC |
|---|---|---|---|---|---|
| Mishra A. | 5 | 3 | 5 | 0.3 | 33 |
| Nasir M. | 5 | 3 | 5 | 0.333 | 81 |
| Risso W. | 5 | 5 | 5 | 0.294 | 450 |
| Shahbaz M. | 5 | 4 | 5 | 0.222 | 180 |
| Abdullah H. | 4 | 2 | 3 | 0.181 | 13 |
| Afonso A. | 4 | 2 | 3 | 0.333 | 12 |
| Alam M. | 4 | 4 | 4 | 0.444 | 28 |

Source: Author's compilation.

Table 3 combines the most relevant authors and their impact measured through the number of publications and h-index, g-index, and m-index. Based on the number of publications, the most pertinent authors are "Hsing Y", "Aizenman J", and "Khan M", having 33, 9, and 8 publications. In terms of h-index, "Aizenman J" is the most impactful author, having at least 8 citations for 8 of their articles out of 9 articles, while the most relevant author, having 33 publications, scored an h-index of 6 only. Hsing Y has been associated with the work in the direction of short-run determinants of the exchange rate, appreciation and depreciation of the exchange rate and their expansionary and contractionary impact, determinants of government bond yield, and the impact of macroeconomic variables on the stock market. Hence, his work can be associated with the direction of macroeconomic variables and their impact. The author "Aizenman J" is associated with exchange rate, interest rate, international reserve, inflation, economic growth, and volatility of middle-income countries, and fundamental and sovereign risk of emerging markets. "Khan M" worked in the field of macroeconomic determinants of "FDI (Foreign Direct Investment), Balance of payment disequilibrium and its correction, stock return, and macroeconomic directions. Hence, the top three authors of this bibliometric analysis can be associated with the above-mentioned field, and their work can be accessed to gain insights into the above-mentioned areas.

If we look at the total citations, we will find that "Brida J" and "Risso W" scored 450 and "Balcilar M" scored 200. Thus, the above table depicts that, based on the criteria used, the ranking of authors differs. Figure 7 is the representation of the author's work time frame; the horizontal line corresponding to the author's name shows the active involvement of the author in research. Hsing Y worked during 2004-2018 and published 33 papers during this time "Aizenman J" worked 2011-2021 and published 9 papers, and "Khan M" published 9 papers.

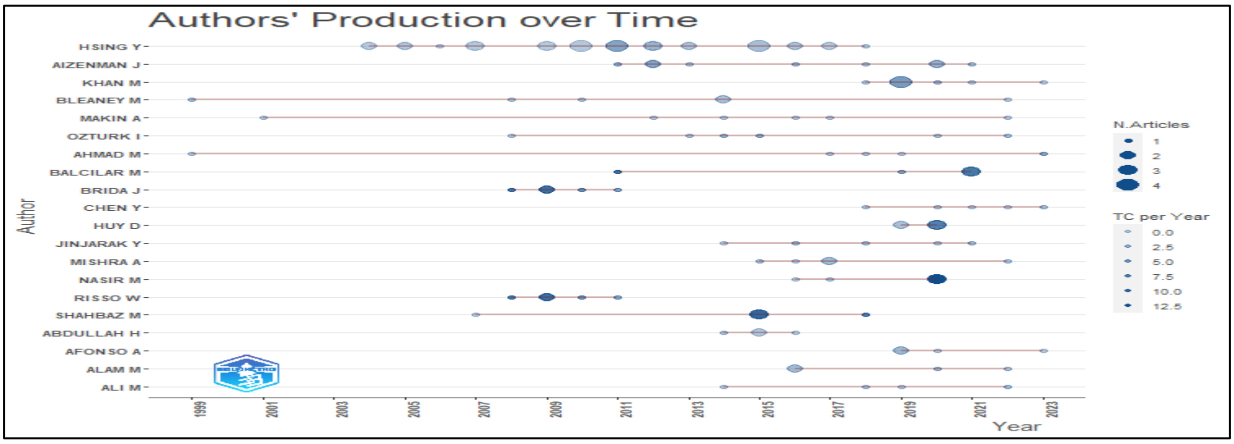


**Figure 7: Author's production over time**

## 4.7. Most Prolific Institution

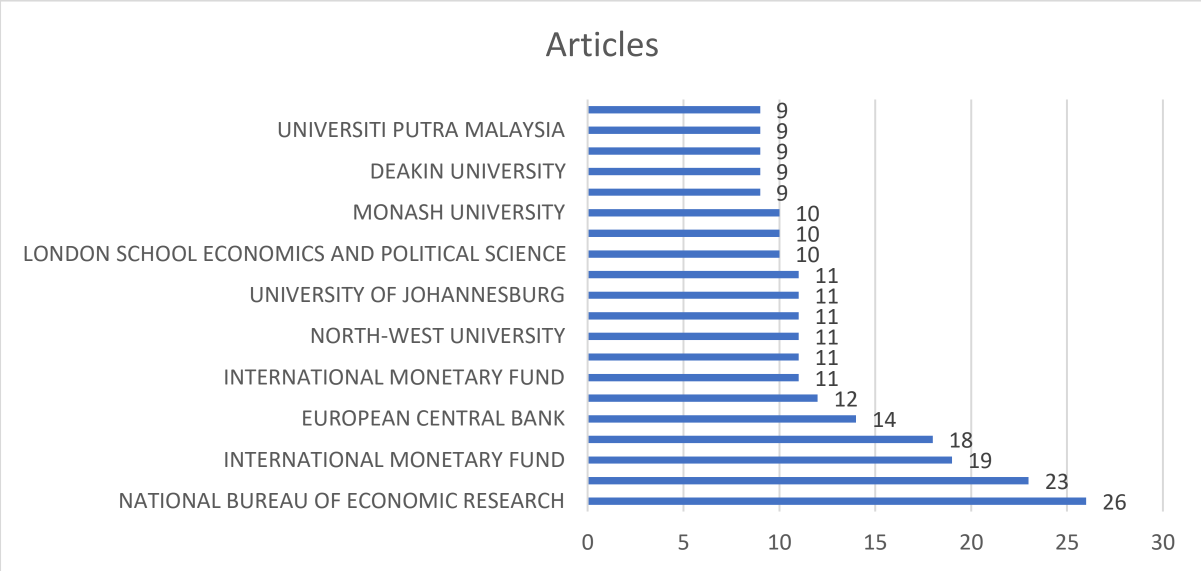


**Figure 8: Most prolific institution**

Figure 8 is created to show the most prolific institution in terms of the number of publications. The "National Bureau of Economic Research" is associated with 26 publications, followed by the "Southeastern Louisiana University" with 23, the "International Monetary Fund" has 19 publications, and the "World Bank" has deposited 18 publications.

## 4.7. Most Relevant Countries

Table 4: Most relevant countries

| Countries | Frequency | Total Citation |
|---|---|---|
| USA | 414 | 5176 |
| China | 166 | 1405 |
| UK | 137 | 994 |
| Germany | 95 | 1002 |
| India | 94 | 518 |
| Turkey | 84 | 520 |
| Nigeria | 81 | 400 |
| Australia | 80 | 667 |
| Malaysia | 69 | 271 |
| Pakistan | 69 | 263 |
| South Africa | 59 | 372 |
| Indonesia | 57 | 79 |
| Brazil | 49 | 150 |
| France | 45 | 538 |
| Italy | 43 | 610 |
| Japan | 43 | 193 |
| Czech Republic | 38 | 149 |
| South Korea | 35 | 130 |
| Portugal | 31 | 315 |
| Iran | 26 | 145 |

Source: Author's Compilation.

The table shows the regional distribution of publications (Freq) and their total citations (TC) in the field of GDP–exchange rate research. The USA leads overwhelmingly (414 publications; 5,176 citations), followed by China (166; 1,405) and the UK (137; 994). The USA's dominance stems from its long-standing leadership in economic research, availability of extensive datasets, and influential institutions such as the National Bureau of Economic Research (NBER) and the IMF (with U.S. linkages), which have historically shaped global macroeconomic scholarship. China's sharp rise reflects its rapid economic integration post-1990s reforms, WTO accession, and growing policy interest in exchange rate management amid export-led growth, making it a hotspot for both domestic and international researchers. The UK ranks third due to its strong academic tradition in economics, internationally reputed outlets (e.g., *Applied Economics*), and London's role as a global financial hub, which naturally fosters research on exchange rate dynamics and monetary policy. Together, these three nations account for the bulk of influential contributions, driven by a mix of research infrastructure, global economic relevance, and policy imperatives, explaining their surge compared to other regions.

## 4.8. Most Frequent Keywords

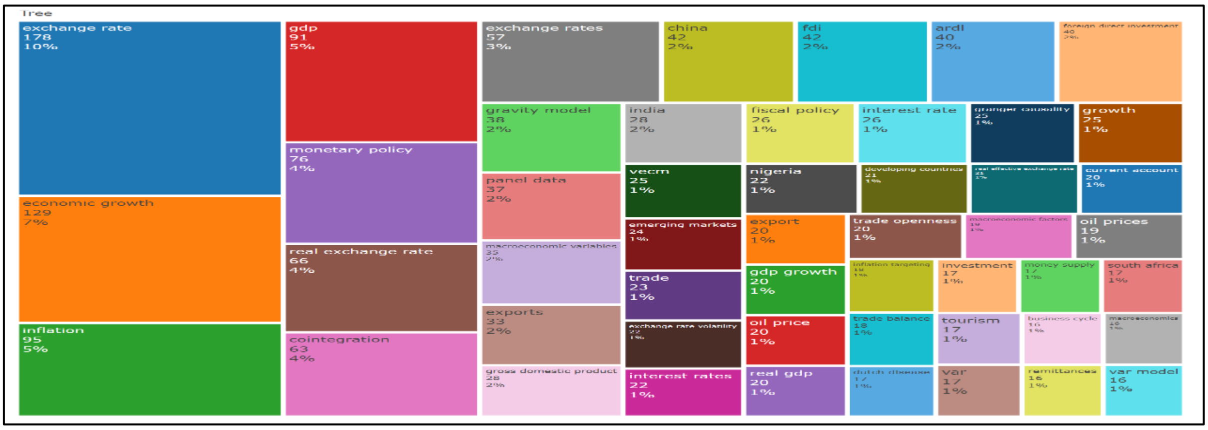


**Figure 9: Treemap of most frequent keywords**

Figure 9 is the colourful representation of the top 50 most frequent authors' keywords. Author keywords refer to significant words and phrases meticulously chosen by the writers of research work to articulate their fundamental nature. The above treemap shows that the term "exchange rate" has been used 178 times by the researcher in the above selected 1808 documents, "economic growth" 129 times, "inflation" 95 times "GDP" 91 times.

**Table 5: Research articles using "GDP" and "exchange rate" pair in keywords**

| Paper title | Author | Source | Total Citations |
|---|---|---|---|
| Research note the tourism growth nexus in Croatia | (Payne & Mervar, 2010) | Tourism Economics | 168 |
| Downscaling and geospatial gridding of socioeconomic projections from the IPCC special report on emissions scenarios SRES | (Gaffin et al., 2004) | Global Environmental Change | 130 |
| The role of oil prices and the real exchange rate in Russia's economy a cointegration approach | (Rautava, 2004) | Journal of Comparative Economics | 110 |
| Impact of oil price shocks on output inflation and the real exchange rate evidence from selected ASEAN countries | (Basnet & Upadhyaya, 2015) | Applied Economics | 69 |

| Paper title | Author | Source | Total Citations |
|---|---|---|---|
| A multiple and partial wavelet analysis of the oil price inflation, exchange rate and economic growth nexus in Saudi Arabia | (Aloui et al., 2018) | Emerging Markets Finance and Trade | 66 |
| On the causes and effects of exchange rate volatility on economic growth, evidence from Ghana, trying to understand the PPPs in ICP 2011 why are the results so different | (Alagidede & Ibrahim, 2017) | Journal of African Business American Economic Journal: Macroeconomics | 49 |
| Research note tourism and growth in the Caribbean, evidence from a panel error correction model | (Apergis & Payne, 2012) | Tourism Economics | 48 |

Source: Author's compilation.

## 4.9. Most Relevant Articles

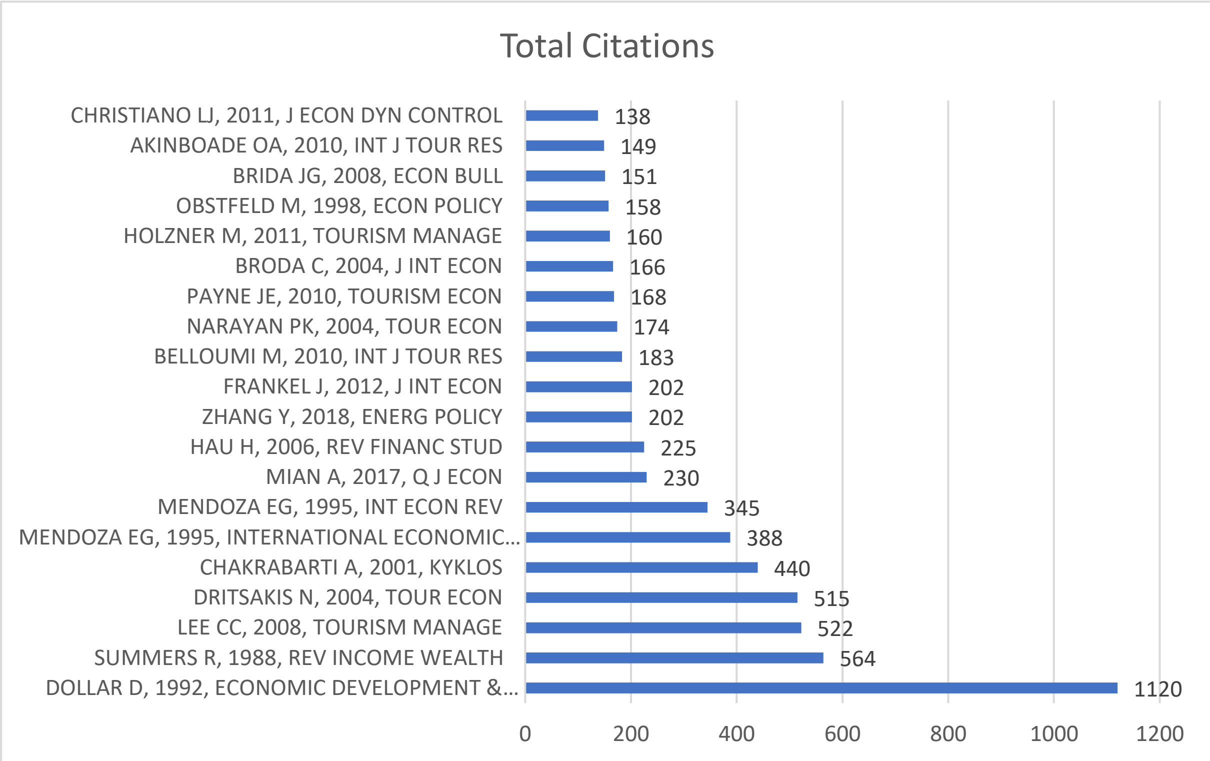


**Figure 10: Most relevant articles based on citations**

Figure 10 is the graphical representation of the most relevant articles along with their total citations. It represents that the article titled "Outward-Oriented Developing Economies Really Do Grow More Rapidly: Evidence From 95 LDCs, 1976-1985" written by (Dollar, 1992) received 1120 citations, followed by "A New Set of International Comparisons of Real Product and Price Level Estimates For 130 Countries 1950-1985" written by (Summers & Heston, 1988) received 564 citations, "Tourism Development and Economic Growth: A Closer Look At Panels" written by (Lee & Chang, 2008) received 522 citations. The above figure shows that out of 1808 articles top 20 articles have achieved citations of more than 100, only one article has crossed the benchmark of more than 1000 citations (1120 citations), while three articles have crossed the benchmark of 500 citations.

## 5. Scientific Mapping

This section contains the qualitative analysis of available data through developing various clusters through the co-word network, collaboration network, thematic analysis, and trend topics, along with thematic evolution.

### 5.1. Co-word Network

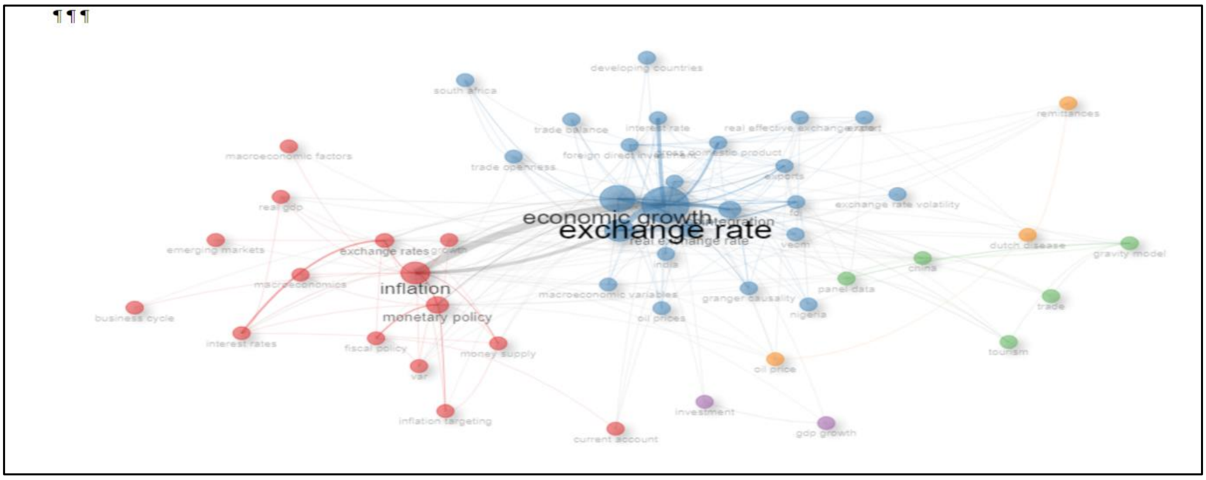


**Figure 11: Co-word network**

The co-word network in Figure 11 highlights exchange rate and economic growth as the central research themes, forming the backbone of the literature. Surrounding clusters reveal diverse but interconnected areas. The blue cluster emphasises the link between exchange rate volatility, trade, foreign direct investment, and growth in developing economies. The red cluster reflects the role of inflation, monetary and fiscal policy, and interest rates in shaping exchange rate dynamics. The green cluster represents country-specific and regional studies (e.g., China, Nigeria) often employing panel data and econometric tools. The orange cluster points to external shocks, such as oil prices, remittances, and Dutch disease, while the purple cluster highlights investment and current account balances as important growth drivers. Overall, the network demonstrates that research has expanded from a narrow focus on bilateral GDP–exchange rate relationships to a multi-dimensional approach incorporating trade, policy frameworks, external shocks, and country-specific contexts. This evolution reflects the increasing complexity and global relevance of exchange rate–growth dynamics.

### 5.2. Trend Topics

The trend analysis represented in Figure 12 reveals an evolutionary trajectory in exchange rate research**.** Initial studies (2006–2010) concentrated on parity conditions and currency crises**,** providing theoretical grounding. As econometric techniques advanced, the 2010–2015 phase emphasized volatility modelling and causal linkages through methods like GARCH, VAR, and cointegration. By 2015–2019, the focus shifted toward - notably the role of exchange rates in GDP growth, trade, inflation, and FDI, particularly in emerging economies such as India and China.

More recently, the literature reflects responses to global shocks (COVID-19) and growing interest in regional development (Sub-Saharan Africa)**.** The prominence of *ARDL* and *panel ARDL* underscores the shift towards models that capture both short- and long-run dynamics across multiple countries. Meanwhile, the increasing frequency of terms such as *public debt* and *external debt* signals heightened concern with the sustainability of growth under exchange rate volatility.

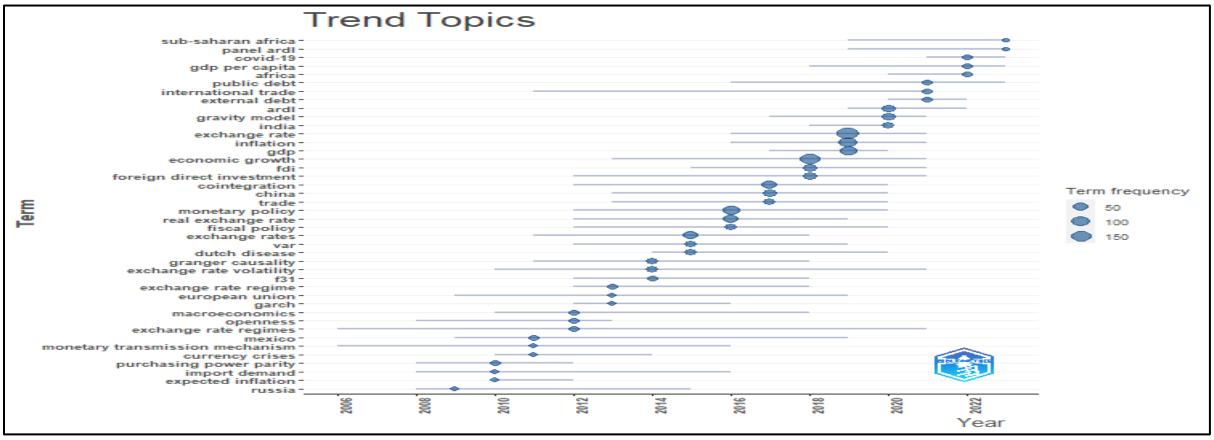


**Figure 12: Trend topics.**

## 5.3. Thematic Analysis

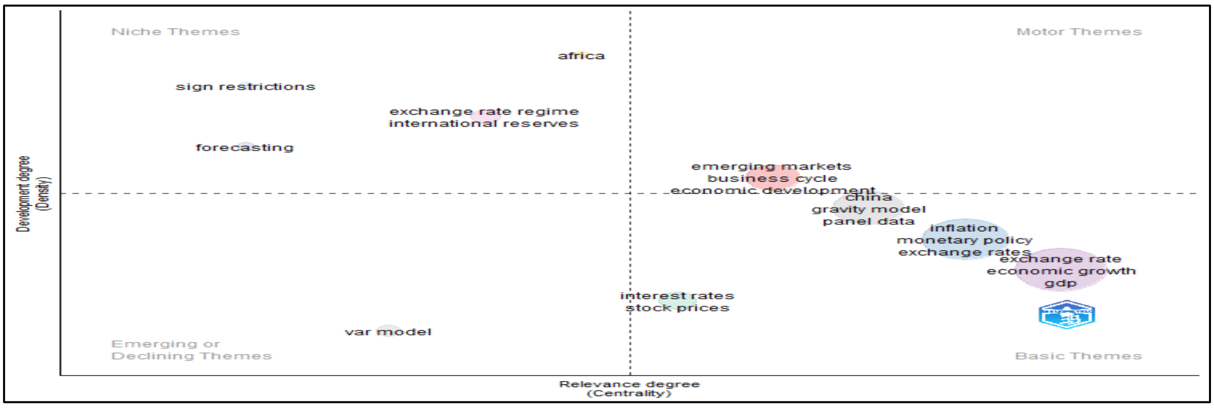


**Figure 13: Thematic analysis**

The thematic map given in Figure 13, divides the list of documents into four themes based on the criteria of centrality and density. Density is a measure of the development of the topic, and centrality is a measure of the relevance (significance) of the topic. Highly developed and significant topics get placed in the motor themes quadrant which contains only one cluster, the Basic themes quadrant contains the clusters which are highly significant but less developed, the Emerging or declining theme box is based on less significant and less developed clusters containing VAR model topic only, and last but not least Niche themes are highly developed but less significant containing four clusters related to exchange rate regime, international reserve; Sign restriction, Africa, and Forecasting.

## 5.4. Thematic Evolution

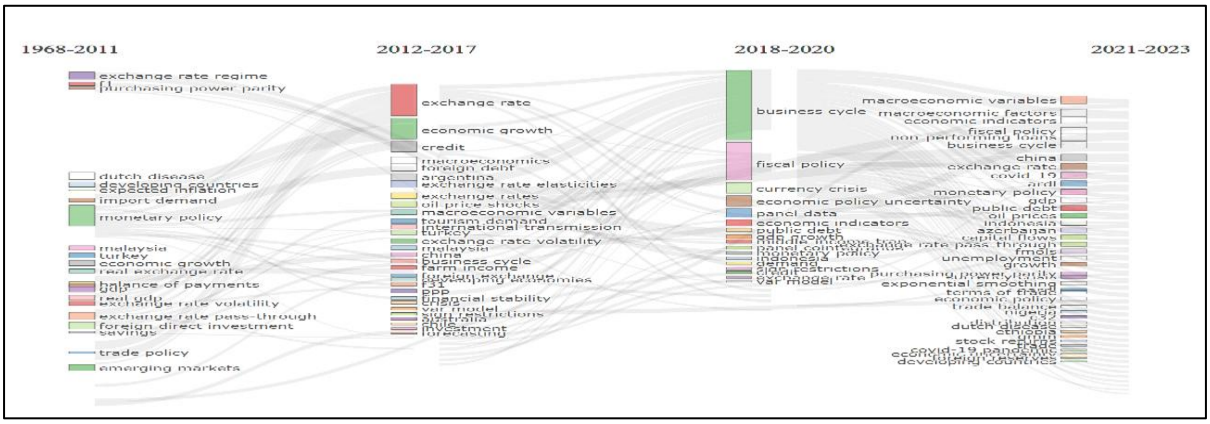


**Figure 14: Thematic evolution.**

Thematic evolution in Figure 14 depicts how the various themes related to research and connected with a particular topic evolved over the period. This study used the data for 1968-2023 and created this thematic evolution which divided the duration of years into four slices 1968-2011, 2012-2017, 2018-2020, and 2021-2023. In the first slice topics of interest were exchange rate regime, purchasing power parity, import demand, monetary policy, exchange rate volatility, Balance of payment, and trade policy. In the second time slice, topics of interest were exchange rate, economic growth, exchange rate elasticities, macroeconomic variables, tourism demand, and international transmission. In the third time slice, the interest of researchers shifted to the business cycle, currency crisis, fiscal policy, economic policy uncertainty, and middle-income trap. In the last time slice, which is the most recent the research interest was in the following topics economic indicators, non-performing loans, COVID-19, public debt, oil prices, trade balance, stock returns and so on.

## 5.5. Co-citation Network of Authors and Journal

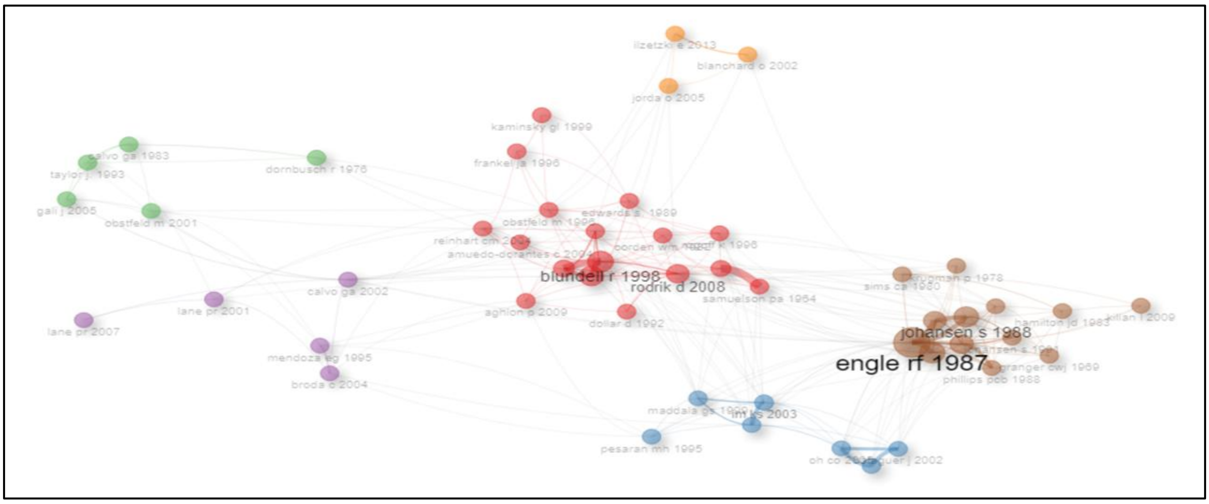


**Figure 15: Co-citation network of authors**

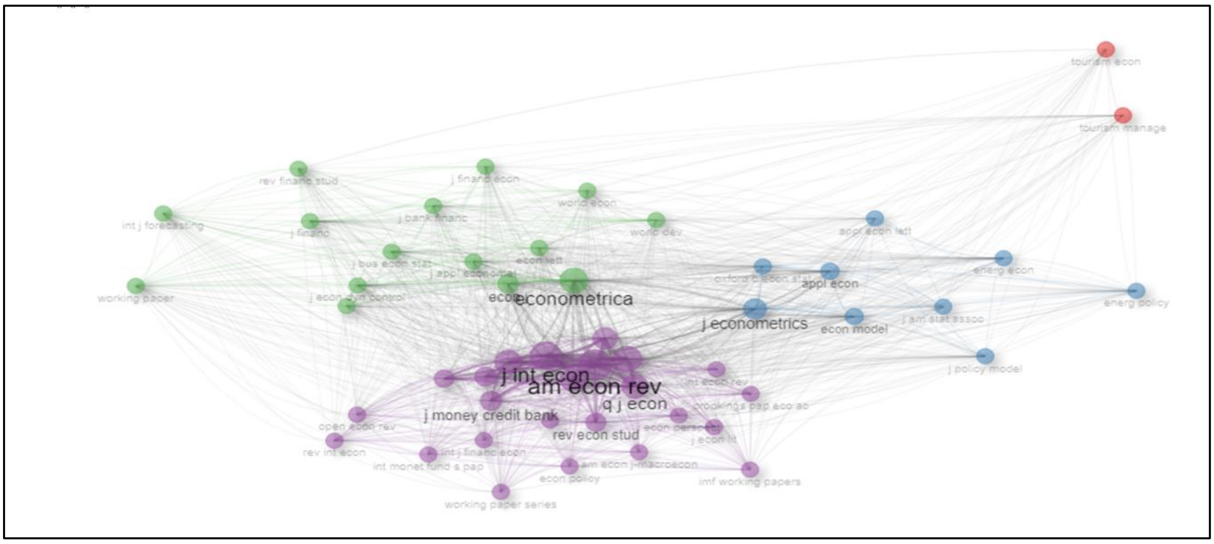


**Figure 16: Co-citation network of Journal**

The frequency with which two authors are mentioned jointly in other documents is known as co-citation. Citing two authors at the same time in a document gives the idea that the cited documents share some similarities and are related to the same area. Figure 15 shows 6 clusters of authors, which means different authors belonging to a particular cluster must have been cited together in various documents. The co-citation network of authors highlights the intellectual structure of research on exchange rates and GDP. The largest nodes, such as Engle RF (1987), Johansen S (1988), and Blundell R (1998), indicate foundational contributions in econometric modelling, cointegration, and dynamic panel methods that underpin much of the empirical work in this domain. Distinct clusters emerge: one focusing on econometric methodology (Engle, Johansen, Granger, Sims), another on macroeconomic policy and growth (Rodrik, Dollar, Edwards, Blundell), and others addressing monetary policy and crisis dynamics (Calvo, Dornbusch, Taylor) or capital flows in emerging markets (Mendoza, Lane, Broda). The interlinkages between these clusters suggest that exchange rate research has evolved through a dual lens—advancing econometric techniques while applying them to pressing policy questions in international economics.

Just like the authors' co-citation network for journals has also been created in Figure 16, which contains four clusters. The co-citation network of journals reveals the intellectual foundation and thematic diversity of exchange rate research. Core economics outlets such as *Econometrica, Journal of International Economics, American Economic Review, and Quarterly Journal of Economics* occupy central positions, indicating their pivotal role in shaping theoretical and empirical developments. Surrounding these are clusters of finance journals (*Journal of Finance, Review of Financial Studies, Journal of Banking and Finance*), applied and policy-focused journals (*Applied Economics, Energy Economics, Journal of Policy Modeling*), and niche outlets such as *Tourism Economics* and *Tourism Management*. This structure suggests that while the field is anchored in mainstream economics, it has extended into applied domains including finance, energy, and tourism, underscoring its multidisciplinary character.

## 5.6.Collaboration Network of Authors, Institutions, and Countries

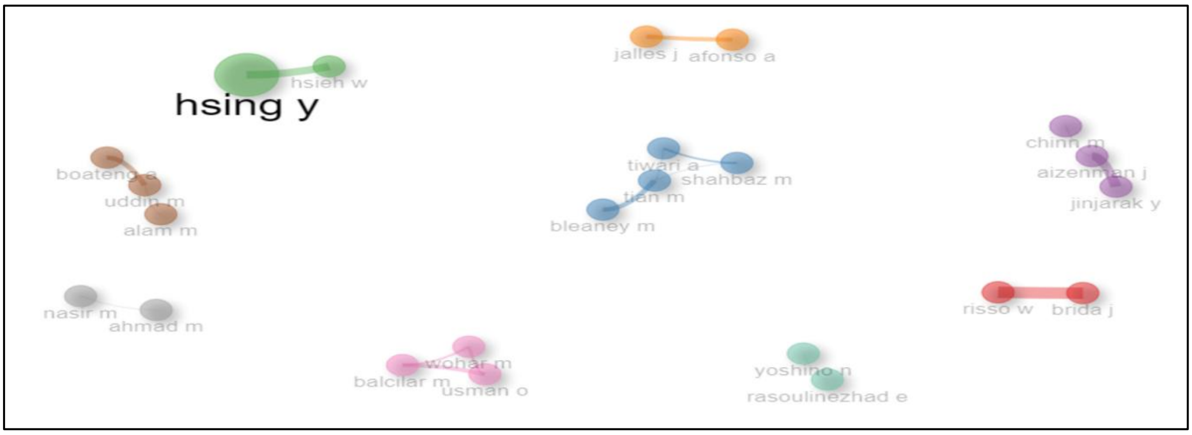


**Figure 17: Collaboration network of Authors**

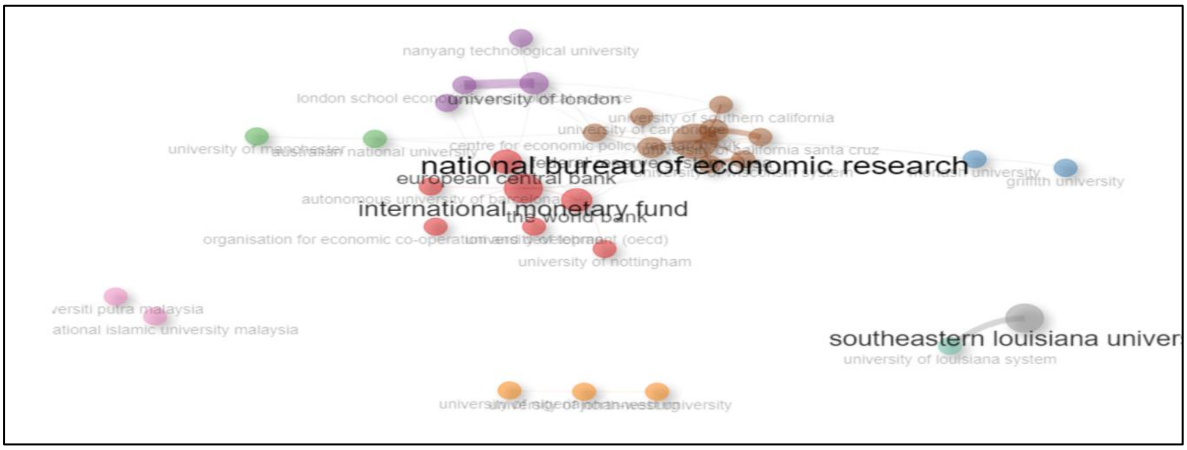


**Figure 18: Collaboration network of Institutions**

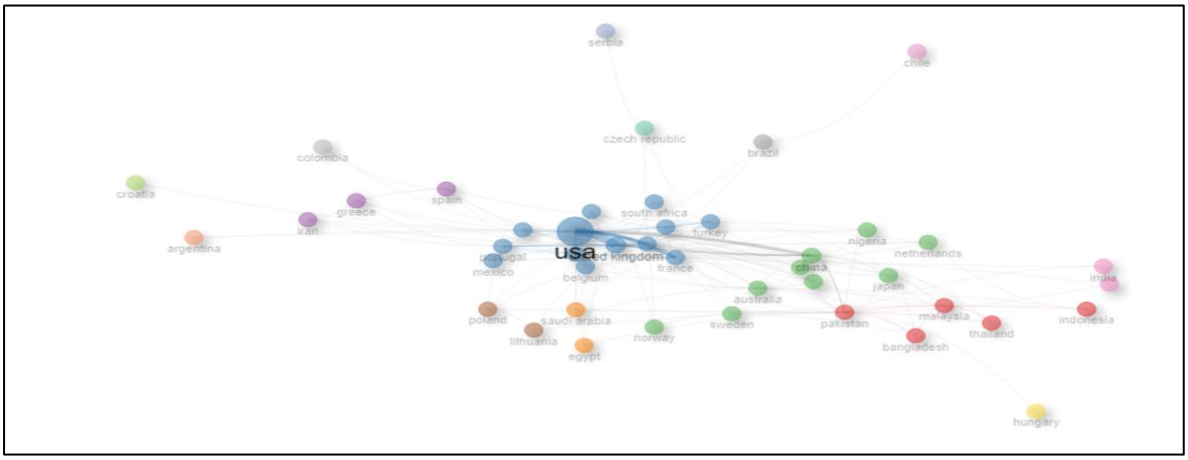


**Figure 19: Collaboration network of Countries.**

The Collaboration network of authors, institutions, and countries has been provided in Figures 17, 18, and 19, respectively. Authors collaborate to do some research on a common topic which interests all the collaborating parties and put the effort which results in quality paper having the contribution of national and international researchers. The collaboration network of authors gave 9 clusters comprising two or three authors in each cluster. The institutional collaboration network also resulted in 9 clusters providing that one of the clusters is made up of all the leading institutions in the world National Bureau of Economic Research, Federal Reserve System – USA, University of California system, University of Cambridge, University of Wisconsin system, University of Southern California, University of Wisconsin Madison, Centre for economic policy research – UK, University of California Santa Cruz. One other cluster is made up of the International Monetary Fund, the European Central Bank, the World Bank, the University of Nottingham, the University of Tehran, the Autonomous University of Barcelona, and the Organisation for Economic Co-operation and Development (OECD). The network showing the collaboration of countries comprises 15 clusters. The largest cluster at the country level is made up of the USA, the United Kingdom, Germany, Turkey, South Africa, France, Italy, Portugal, Switzerland, Canada, Mexico, New Zealand, and Belgium.

## 6. Findings and Conclusion

This study provides a comprehensive bibliometric and scientific mapping of research on the exchange rate–GDP nexus over the period 1968–2023. The analysis of 1,799 documents from Scopus and Web of Science highlights the steady growth of scholarly output in this field, particularly after the 1990s, reflecting the increasing global relevance of exchange rate dynamics in shaping economic performance. Journals such as *Economic Modelling, Applied Economics,* and *Journal of International Money and Finance* have emerged as central publication outlets, while authors including Hsing Y and Aizenman J, along with institutions such as the International Monetary Fund and the National Bureau of Economic Research, have played pivotal roles in advancing the field.

The scientific mapping results reveal that dominant themes have centred on exchange rate, economic growth, inflation, monetary policy, and stock prices, whereas emerging and niche themes such as international reserves, exchange rate regimes, and forecasting remain relatively underexplored. Thematic evolution further indicates a shift from earlier concerns with purchasing power parity, Dutch disease, and trade policy toward more contemporary issues involving capital flows, exchange rate pass-through, GDP, and unemployment. Co-citation analyses of authors and journals demonstrate that the intellectual structure of this field is anchored in econometric methodology and macroeconomic theory while extending into applied domains such as finance, energy, and tourism.

Overall, the findings highlight both the maturity and fragmentation of the literature. While the field has established a robust foundation, significant opportunities remain to expand research on underdeveloped themes, strengthen institutional and international collaborations, and adopt integrative methodologies such as systematic literature reviews and meta-analyses. By addressing these gaps, future scholarship can advance the theoretical and empirical understanding of the exchange rate–GDP nexus and provide evidence-based insights to policymakers navigating an increasingly volatile global economic environment.

This current study is merely the quantitative analysis of available literature in the field of exchange rate and Gross Domestic Product. Qualitative insight has been incorporated into this study with the help of scientific mapping, which is not enough to draw the themes of various studies; forming a collaboration network based on different themes such as co-citations, collaboration analysis and thematic analysis. This study can provide a base for future studies conducting meta-analyses in this field. This analysis is based on the sources indexed in Scopus and Web of Science, so documents of good quality published in sources out of the scope of Web of Science and Scopus are out of the scope of this study.

## 7. Proposed Research Directions

Future research on the GDP–exchange rate nexus should move beyond identifying associations and focus on addressing questions with clear theoretical and policy relevance. First, while existing studies have documented exchange rate volatility and its correlation with growth, relatively little is known about the transmission mechanisms through which shocks to currency markets translate into long-run output dynamics. Filling this gap is critical for developing robust macroeconomic models that guide monetary and exchange rate policy, particularly in emerging markets vulnerable to external shocks.

Second, the literature gives limited attention to the interaction between exchange rate regimes, external debt, and fiscal sustainability. As many developing economies face rising debt burdens, understanding these linkages has strong policy significance for debt management and exchange rate stabilization strategies**,** offering governments evidence-based guidance on designing sustainable macroeconomic frameworks.

Third, the impact of global crises such as COVID-19 and financial contagion episodes remains an emerging field. Analyzing how such shocks alter the exchange rate–growth relationship would enrich crisis management theory and equip policymakers with tools to enhance resilience in an era of heightened uncertainty.

Finally, the rise of advanced econometric methods—such as panel ARDL, machine learning forecasting, and high-frequency data models—provides an opportunity not merely for methodological innovation but for testing the validity of existing theories under new conditions. Doing so can help reconcile competing perspectives on the directionality of the exchange rate–GDP relationship and refine policy prescriptions for both advanced and developing economies. Along with the above-mentioned fields, institutional and scholarly collaboration needs to be strengthened, as the current output is concentrated in a few institutions and the author network remains fragmented; stronger partnerships would enhance the depth, credibility, and policy relevance of findings. Together, these directions would move the field toward greater theoretical maturity, empirical robustness, and practical utility for policymakers.

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Promoting Research

# Customer Loyalty in the Age of Sustainability: A Moderated and Mediation Model of Attitude, Perception, and Risk-Perception

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**JEL Classification**
M10, M31, Q01

**Abstract:** Environmental sustainability has stem as a key component for modern business. In accordance, this research work investigates the relationship of customers' green perception, attitude, and risk-perception with their green-loyalty within the green marketing and sustainability settings. Data from 461 shoppers through a questionnaire are collected and analyzed using co-variance-based SEM in Amos v24. Results show that customers' green perception substantially influences their green-loyalty and their attitude toward sustainability, which positively influences customers' green-loyalty. Further, customers' attitude toward sustainability mediates the effect of green perception on their green-loyalty. Besides, the risk-perception does not moderate the effect of green perception and attitude on customers' green-loyalty, nor does it moderate the influence of perception on attitude. Rarely has any study examined the moderated mediation approach of risk-perception within the relationships among customers' perception, attitude, and loyalty in the context of greenness and sustainability. The outcomes of this study highlight the social implications that sustainable development of mankind is possible by developing a green attitude and perception.

## 1. Introduction

Customers are becoming more consistent in their evaluation for their shopping activities by learning the trade-off rules among the attributes (Ahn et al., 2013), where behavioural precursors differ across the retail formats for developing green-loyalty in the emerging market scenario, posing a task for retailers in their effort to attract, satisfy & bind customers with them (Dabija et al., 2018). This might be the reason for which customers, especially millennials, prefer brands that embrace purpose and sustainability (White et al., 2019), which is reflected in the Indian economy, which has expressed strong concern about environmental issues, as the country's policymakers have set directives for making India's development efforts more environmentally friendly (Bhatnagar et al., 2022). Businesses are realizing more and more the significance of integrating ecological considerations into their marketing strategies, as studies have shown that environmental awareness, environmentally friendly product features, environmentally conscious promotion, and pricing improve, so does green buying behavior among Indian customers and it also demonstrates that customers are now keen to pay higher for goods that are eco-friendly in nature to battle the ecological pollution that is harming our planet as technology and industrialization advance (Boztepe, 2012). Therefore, the initiatives that are typically considered to be decreasing profit for less environmentally friendly businesses can benefit all businesses under certain situations, such as raising awareness of customers of sustainability differences whether by the business or another entity, enhancing the percentage of customers that care about sustainability at all, or cutting the expense to produce more sustainable goods (Galbreth & Ghosh, 2013). Thus, in light of these trends, it is important to study the subsequent research issue.

This study goes with defined concepts of green perception, sustainability, green loyalty, and risk perception. Hence, we referred the following definitions. Green perception mainly describes a person's awareness, understanding, and attitude toward environmental concerns, conservation efforts, and behaviours or policies related to sustainable development (Duque Oliva et al., 2021). Sustainability in the context of marketing management, can be referred through "triple bottom line" approach developed by Elkington (1994), where the business is suggested to be considered/judged on planet, people, and profit. Green loyalty refers to the degree of consumers' intention to repurchase, influenced by strong ecological attitude and commitment to sustainability toward a specific brand, product, service, company or group (Chen, 2013). Risk perception refers to an individual's beliefs about potential danger or the likelihood of experiencing a loss, involving subjective judgments about the nature and seriousness of the risk (Darker, 2013). The above two phases of discussions set the context for this study's research problem.

Whether the customers' green-loyalty depend on their perception towards green products and attitude towards sustainability with the moderating role of risk-perception?

## 2. Review of Literature

### 2.1. Perception towards green products leads to customers' green-loyalty

Customers' perceptions of value are improved when they perceive a higher level of product quality, which strengthens their desire to make a purchase, and increases the perceived value of green items (Wu & Chen, 2014). Additionally, customers' perceived emotional, functional, & social values have a substantial positive impact on their satisfaction related to eco-conscious innovation, where satisfaction leads to their loyalty with reduced sensitivity to price (Hur et al., 2013), where quality, trust, attitude, perception & loyalty of buyers for eco-friendly goods are meaningfully connected (Baktash & Talib, 2019). So, behavioural intention of customers can be driven by brand image that build on green reputations, which shows that eco-friendly practices can create a positive perception, consequently the reputation & image of business in the eyes of the customers (Yadav et al., 2016). Although, consumption values partially influence the green satisfaction of customers, which in turn, affects their green loyalty & trust (Issock et al., 2019), customers are more prosocial by not reacting negatively to ecological product failures because doing so could jeopardize the success of a product that would otherwise benefit society and the environment. (Tezer et al., 2023). These facts demand that customers green-perception should be strategically connected to the green-loyalty, which is designed as a proposition (H1) of this study.

### 2.2. Perception towards green products builds attitude towards sustainability

Customers prefer ecological products having environmental concerns encompassing three dimensions like eco-friendliness, eco-efficiency, & sustainable lifestyle where the latter significantly shapes their perceptions (Christopher et al., 2023), which implies that customers eagerly pursue environmentally friendly products that adhere to and incorporate sustainability principles when they are cognitively aligned towards them and have positive experiences regarding environmental protection (Dabija & Bejan, 2018). In addition to this, customers' sociodemographic characteristics influence their awareness of concepts linked to environmental sustainability, and a significant gender effect influences customers' thoughts regarding the importance of labels that disclose desired information, narrative components that specify the types & details of packaging, information about the country of origin of products, along with environmental footprint carry more importance for women than men (Chirilli et al., 2022). So, ecolabels significantly mold the ecological awareness & attitude of millennials buying eco-friendly products (Carrión-Bósquez, 2024). Further, awareness of sustainable design benefits, & environmental knowledge is building sustainable customer behavior & environmental attitudes (Horani, 2020). However, customers' perception that ecological products are costly along with insufficient information & reluctance to pay extra for eco-sensitive options creates a monetary challenge, restricting the broad implementation of sustainable practices (Lima et al., 2024). So, it is possible to conclude that a link exists between green-perceptions and attitudes toward sustainability, which emerged as a proposition (H2) of this study.

### 2.3. Attitude toward sustainability arouses green-loyalty of customers

Customers buying decisions are strongly influenced by sustainability & social impact, and they are more faithful towards brands that follow ethical practices (Sanitha, 2025) where their personal norms and attitude are being strongly affected by environmental concerns and awareness of consequences, which in turn mediate purchase intentions for eco-friendly products (Siddhpuria et al., 2025). Further, both environmental attitudes and brand image positively influence decisions to buy products with eco-conscious packaging (Metekohy et al., 2024). In line with the discussion, firms can capitalise on their products' environmental characteristics for branding purposes with environmentally sustainable packaging, avoiding unnecessary paper & plastic (Majeed et al., 2022). Therefore, the attitude toward environmentally conscious behavior having green image can build green customer loyalty & satisfaction (ÇavuĢoğlu et al., 2020), which implies customers' awareness & ecologically conscious attitudes have a noteworthy effect on their eagerness to buy eco-conscious products (Shehawy & khan, 2024). Thus, customers' positive attitude toward environmental safeguarding will encourage them to prefer & search for sustainable product retailers (Dabija & Bejan, 2018). So, it can be inferred that customers show interest in products and services sustainability that they consume. They are also keen to utilize & assess factual evidence that is available to opt for eco-conscious product choices. However, they face a shortage of credible factual evidence, and believe that data-finding is time-consuming (Vehmas et al.,2024). Nonetheless, customers who care about the environment stick with their favourite brands even after sustainability is introduced (Kuchinka et al., 2018). So, this study makes a proposition (H3) that customers' attitude towards sustainability can lead to their green-loyalty.

### 2.4. Attitude toward sustainability mediates the effect of 'Perception towards green products' on customers' green-loyalty

Although, quality & trust substantially impact customer attitude & loyalty (Baktash & Talib, 2019), customers with minimal academic qualifications show limited sustainability awareness & concerns; older age groups demonstrate less awareness of sustainability & its associated issues; and earning level shows ambiguous outcomes, whereas gender does not affect attitude towards sustainability (Sánchez-Bravo et al., 2020). So, it can be said that customers' perception of eco-friendly actions significantly influences their attitudes towards the business, where the green image acts as a mediator between eco-friendly actions and their attitudes (Vinicio Jaramillo-Cuenca et al., 2021). Further, credible ecolabels positively influence attitude towards eco-friendly product purchase (Riskos et al., 2021), which can shape customers attitude towards sustainability and arouse green-loyalty among them. Furthermore, attitudes toward sustainability can be favorably impacted by sustainability of an area & sustainability education (Fanea-Ivanovici & Baber, 2022). Therefore, to stay afloat in globally competitive marketplaces, commercial firms must emphasize & promote the eco-friendly benefits of their goods & services (Freze & Nurova, 2021). Hence, a proposition (H4) is made by this study that attitude towards sustainability can mediate the effect of green-perception on green-loyalty.

### 2.5. Role of risk-perception within the relationship of customers' perception, attitude, and loyalty in the context of greenness and sustainability

For the customers of natural products, the quality of details regarding greenness significantly predicts green brand love & trust, where the information's cogency, wholeness, & credibility influences directly & indirectly the brand love via the underlying mechanism of environmentally conscious brand trust (Taufik, 2023). However, aspects like confinements in environmental awareness, pricing, risk-perception, business image, trust, & keenness to pay make the inconsistency between customer attitudes and their real buying trends of eco-friendly goods (Sharma, 2021). So, customer value and image of oneself positively influence the degree of satisfaction and intention, while risk-perception has a contrary effect, rejecting the impact of ideal self-image and switching expenses (Nguyen-Van, 2024). Thereby, it can be inferred that the attitude of customer influences their sustainable consumption where ecological consumption value mediates the connection between customer attitude & their eco-conscious shopping behavior (Jose et al., 2022). Furthermore, the perception of environmentally conscious values is positively correlated & the green risk-perception is adversely correlated to the interest in buying eco-friendly goods (Dhewi et al., 2018). Moreover, risk-perception and ecological guideline have substantial impacts on customers' readiness to participate in eco-sensitive behaviors where ecological guidelines can favourably adjust risk perception to improve their keenness to involve in such behaviors (Li et al., 2022). Thus, the incorporation of green trust & green risk-perception can increase the prediction of loyalty towards ecological products (Pahlevi & Suhartanto, 2020). So, it can be said that higher ecological risk perception, societal expectations, knowledge about environment, & health-oriented mindset become the precursors of behavioral intention towards sustainability, which leads to sustainable consumption-behavior (Ghaffar & Islam, 2023). From the above discussions, a proposition (H5) can be developed that there is a role of risk-perception within the relationships of perception and attitude on the ground of greenness.

Based on the above discussion, the following objectives are set for the study:

- To identify and confirm major dimensions of customers' perception and attitude in the context of greenness and sustainability.
- To examine the relationship of customers' green perception, attitude towards sustainability with their green-loyalty.
- To study the role of customers' risk-perception within the relationship of customers' green perception, attitude towards sustainability, and green-loyalty.
- To develop some marketing strategies to build and strengthen customers' green-loyalty towards green and sustainable products.

Aligning with the objectives, the literature review prompts the ensuing hypotheses as follows:

**H1:** Customers' green perception has a positive effect on their green-loyalty.
**H2:** Customers' green perception has a positive effect on their attitude towards sustainability.
**H3:** Customers' attitude towards sustainability has a positive effect on their green-loyalty.
**H4:** Attitude toward sustainability significantly mediates the effect of perception towards green products on green-loyalty.
**H5:** Customers' risk-perception moderates the effects of customers' green-perception on their attitude; on their loyalty; and moderates the effect of customers' attitude toward sustainability on their green-loyalty.

## 3. Research Methodology

This research employs an experimental design in which causal relationships among customers' green perception, attitude toward sustainability, risk-perception, and green-loyalty are scrutinized. The loyalty of customers mainly in the organized retail sector is measured, in the terms of greenness and sustainability. A structured questionnaire based on a five-point Likert scale is distributed to 461 individual shoppers which was collected from the month of May 2024 till October 2024. This questionnaire consists of 39 items, out of which 16 items are related to customers' green perception; 14 items are related to customers' attitude towards sustainability; 3 items are related to customers' green-loyalty, and 6 items are related to demographic variables of shoppers. This study implemented a stratified sampling technique, with four geographical areas of Odisha treated as four strata that are Northern Odisha (114 samples), Central Odisha (119 samples), Western Odisha (121 samples) and Southern Odisha (107 samples).

Data analysis is initiated with scale reliability testing and progresses to structural equation modeling (SEM). Prior to assessing the structural model, two measurement models comprising customers' green perception (CuGP) and customers' attitude toward sustainability (CuAS), each with three constructs are validated through confirmatory factor analysis (CFA). This step ensures the constructs are accurately measured based on indicators from the literature review, employing second-order CFA. Subsequently, the moderating effect of risk-perception is tested within the described structural relationship, in accordance with Hayes' model-59. Data analyses are performed using SPSS 27.0, AMOS 24.0, Process-Macro, and Mendeley Desktop for referencing and citations.

**Conceptual framework**

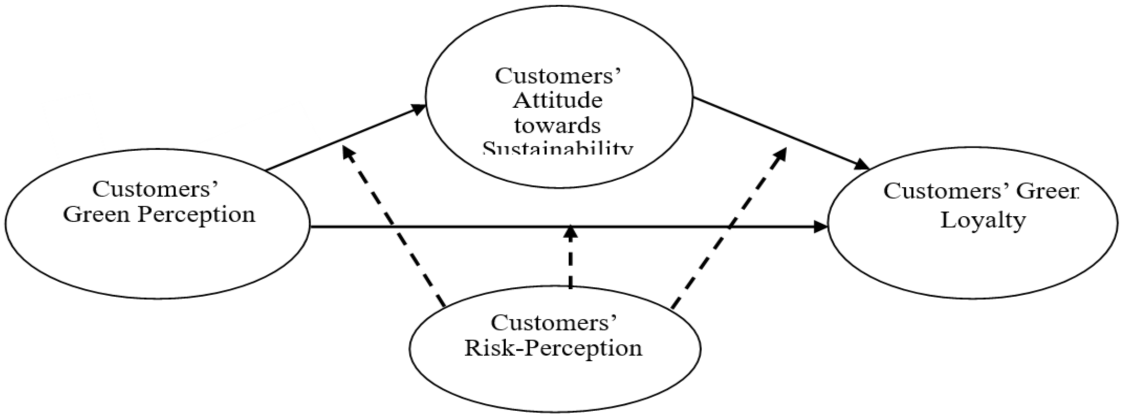


**Figure 1: Green loyalty on perception-attitude interaction for green-ness & sustainability**

Figure 1 illustrates the proposed structural model, depicting the hypothesized relationships among key constructs. Customers' green perception is positioned as an antecedent to both attitude towards sustainability and customers' green loyalty, where attitude toward sustainability further influences customer loyalty, forming a sequential pathway. Risk perception is modeled as a moderating variable represented by a dashed line to indicate its conditional role. The model reflects the theoretical framework guiding this study, integrating perception, attitude, and loyalty within the green & sustainability context.

## 4. Results and Discussion

### 4.1. Reliability of the Scale

This study's scale demonstrates internal consistency reliability at 95% (as evidenced by a Cronbach's alpha of 0.948 with standardized items), based on 38 items excluding 6 demographic variables. Thus, the structured questionnaire achieves 'excellent' reliability (George & Mallery, 2006), with a mean score of 146.38 and a standard deviation of 22.510. The above statistics indicate an overall positive response trend and standard deviation suggests moderate dispersion, implying some variability in respondent agreement across items. This suggests that respondents generally agreed with the scale items, reflecting favorable perceptions toward the measured constructs.

### 4.2. Sample Profile

The sample consists of approximately 42% female and 58% male respondents. The age distribution reveals that the largest segment, about 60%, comprises individuals under 30 years old, followed by 35% of middle-aged customers (up to 50 years old), and 5% senior citizens (above 50 years old). Marital status specifies that 66% of individuals are single, while 34% are married. In terms of educational background, 1% have an intermediate level, 15% are undergraduates, 53% possess postgraduate degrees, and nearly 31% have an education higher than a postgraduate level. Regarding employment status, around 14% work for government agencies, 54% for private organizations, nearly 6% are business owners, 5% are students, and 21% are engaged in other types of employment. Income distribution shows that the low-income group (up to 30,000 INR) constitutes nearly 39% of the sample, the mid-income group (up to 70,000 INR) makes up 37%, and the high-income group (above 70,000 INR) represents 24%.

### 4.3. Measurement Model of Customers' Green Perception (CuGP)

This measurement model of CuGP carries three constructs WiGP (Willingness to pay more for green products); QuGP (Quality of green products); and ReGP (Recycling nature of green products) carrying five, six, and five indicators respectively, according to the scale of Isaacs (2015) and is tested through CFA.

Statistical inferences indicate that the model-fitting of CuGP is acceptable, as the fit-indices are meeting the cut-off criteria. For instance, corresponding values of GFI (.924), NFI (.916), RFI (.901), IFI (.944), TLI (.933), & CFI (.943) are exceeding .9 (Hair et al., 2013; Hu & Bentler, 1998). The CMIN/DF value (2.885) is below the threshold of 3 (Schreiber et al., 2006); the SRMR value (.0427) is lesser than .08 (Hu & Bentler, 1999); and RMSEA value (.064) is between .06 and .08 (Schreiber et al., 2006).

## 4.4. Measurement Model of Customers' Attitude towards Sustainability (CuAS)

This measurement model of CuAS have three constructs, namely CuSK (Sustainability Knowledge), CuSD (Sustainability Decision), and CuSF (Sustainability Feeling), each with five, five, and four indicators, according to the scale of Zhang et al. (2021), is also tested through CFA. This scale and the scale of preceding measurement model are adopted with respect to the relevance (greenness) of the present study.

Model-fitting of CuAS is acceptable as the fit indices meet the cut-off criteria. Specifically, the values of GFI (.929), NFI (.933), RFI (.917), IFI (.954), TLI (.943), & CFI (.954) are exceeding .9 (Hair et al., 2013; Hu & Bentler, 1998); the CMIN/DF value (2.987) is below the threshold of 3 (Schreiber et al., 2006); the SRMR value (.0420) is lesser than .08 (Hu & Bentler, 1999); and the RMSEA value (.066) is between .06 and .08 (Schreiber et al., 2006).

## 4.5. Reliability and Convergent Validity of both Measurement Models (CuGP and CuAS)

Every construct (WiGP, QuGP, & ReGP; CuSK, CuSD, & CuSF) of both measurement models are tested for reliability & convergent validity according to Straub et al. (2004) suggestion and results are displayed in table1.

**Table 1: Reliability and Convergent Validity of constructs of both CuGP & CuAS**

| **Customers' Green Perception (CuGP)** | | | | **Customers' Attitude towards Sustainability (CuAS)** | | | |
|---|---|---|---|---|---|---|---|
| Construct-indicator relationships | β | 't' | α & CR | Construct-indicator relationships | β | 't' | α & CR |
| **WiGP** | | | | **CuSK** | | | |
| Cgp1 | .710 | --- | .844 & .844 | Cas1 | .735 | --- | .862 & .863 |
| Cgp2 | .710 | 13.541* | | Cas2 | .712 | 13.918* | |
| Cgp3 | .711 | 13.737* | | Cas3 | .724 | 14.500* | |
| Cgp4 | .716 | 13.654* | | Cas4 | .770 | 15.376* | |
| Cgp5 | .758 | 13.881* | | Cas5 | .793 | 16.678* | |
| **QuGP** | | | | **CuSD** | | | |
| Cgp6 | .736 | --- | .873 & .873 | Cas6 | .738 | --- | .860 & .860 |
| Cgp7 | .714 | 14.680* | | Cas7 | .805 | 16.329* | |
| Cgp8 | .731 | 14.867* | | Cas8 | .737 | 14.864* | |
| Cgp9 | .769 | 15.727* | | Cas9 | .712 | 14.679* | |
| Cgp10 | .711 | 14.431* | | Cas10 | .716 | 14.566* | |
| Cgp11 | .721 | 15.017* | | | | | |
| **ReGP** | | | | **CuSF** | | | |

| Customers' Green Perception (CuGP) | | | | Customers' Attitude towards Sustainability (CuAS) | | | |
|---|---|---|---|---|---|---|---|
| Cgp12 | .761 | --- | | Cas11 | .743 | --- | |
| Cgp13 | .738 | 15.732* | .858 | Cas12 | .749 | 15.272* | .852 |
| Cgp14 | .746 | 14.223* | & | Cas13 | .762 | 15.489* | & |
| Cgp15 | .744 | 15.150* | .858 | Cas14 | .820 | 16.720* | .853 |
| Cgp16 | .710 | 14.698* | | | | | |
| **CuGP (2$^{nd}$ order construct)** | | | | **CuAS (2$^{nd}$ order construct)** | | | |
| WiGP | .529 | --- | .895 | CuSK | .826 | --- | .908 |
| QuGP | .980 | 6.321 | & | CuSD | .755 | 9.895* | & |
| ReGP | .615 | 7.713 | .765 | CuSF | .800 | 9.738* | .837 |

't' is the value of critical ration (CR); β - Standardised regression weight; α - Cronbach's Alpha; WiGP: Willingness to pay more for green products; QuGP: Quality of green products; ReGP: Recycling nature of green products; CuSK: Sustainability Knowledge; CuSD: Sustainability Decision; CuSF: Sustainability Feeling; *Significant at 1% level of significance; --- Pre-fixed regression weight as 1

Source: Authors' compilation.

Cronbach's alpha values and composite reliability (CR) values for all the constructs exceeds 0.7 (Hair et al., 2013) which indicates the acceptable reliability for both measurement models. Concurrently, convergent validity is also acceptable for these two measurement models with the lowest factor-loadings (.711, .711, .704, & .724; .741, & .744) for the constructs (WiGP, QuGP, & ReGP; CuSK, CuSD & CuSF) of CuGP and CuAS respectively surpassing 0.7 (Henseler et al., 2009); and all AVE values exceeding 0.5 (Bagozzi & Yi, 1988). These threshold values not only meet statistical criteria but also affirm the theoretical robustness of the constructs, where more the β-value, stronger is importance of respective indicator on construct. They confirm that green perception, attitude towards sustainability, and green loyalty are internally consistent and conceptually distinct. Further, significant 't' for every indicator at 1% level of significance proves the precision of the model composition (table1).

## 4.6. Discriminant Validity of both Measurement Models (CuGP and CuAS)

All six constructs are tested for the discriminant validity of both measurement models and results are presented in table 2.

**Table 2: Discriminant validity of constructs of CuGP & CuAS**

| Constructs of CuGP | Mean | SD | AVE | MSV | ASV | Max R(H) | WiGP | QuGP | ReGP |
|---|---|---|---|---|---|---|---|---|---|
| **WiGP** | 3.289 | .675 | .520 | .269 | .194 | .845 | **.721** | | |
| **QuGP** | 4.098 | .749 | .534 | .407 | .338 | .874 | .519* | **.731** | |
| **ReGP** | 3.902 | .682 | .548 | .407 | .263 | .859 | .345* | .638* | **.740** |
| **Constructs of CuAS** | | | | | | | CuSK | CuSD | CuSF |
| **CuSK** | 3.399 | .674 | .559 | .436 | .412 | .866 | **.747** | | |
| **CuSD** | 3.386 | .718 | .551 | .389 | .377 | .863 | .624* | **.742** | |
| **CuSF** | 3.531 | .684 | .592 | .436 | .400 | .856 | .660* | .604* | **.769** |

SD: Standard Deviation, AVE: Average Variance Extracted; MSV: Maximum Shared Variance; ASV: Average Shared Variance; CuGP: Customers' green perception; CuAS: Customers' Attitude towards Sustainability; WiGP: Willingness to pay more for green products; QuGP: Quality of green products; ReGP: Recycling nature of green products; CuSK: Sustainability Knowledge; CuSD: Sustainability Decision; CuSF: Sustainability Feeling, *Inter-construct co-relationship is significant at 1% level of significance.

Source: Authors' compilation.

Discriminant validity for both the measurement models is proved as the square root of AVE (diagonal values in bold) for each construct (Table 2) of customers' green perception, and customers' attitude towards sustainability are exceeding the respective inter-construct co-relationships; and values of both ASV & MSV are lower than the respective AVE values (Fornell & Larcker, 1981). Additionally, the values of Max R(H), and maximal reliability of all constructs are above 0.8 (Hancock & Mueller, 2001). The mean and standard deviation (SD) values of all constructs reflect their statistical nature. For the practical implications also, the above constructs can be treated distinctly.

## 4.7. Testing Structural Model

According to the two-step recommendation (Anderson & Gerbing, 1988), the structural model (figure-3) is tested by SEM (Structural Equation Modelling) approach after testing two measurement models. The structural model includes 16 indicators of CuGP, 14 indicators of CuAS, and 3 indicators of CGL.

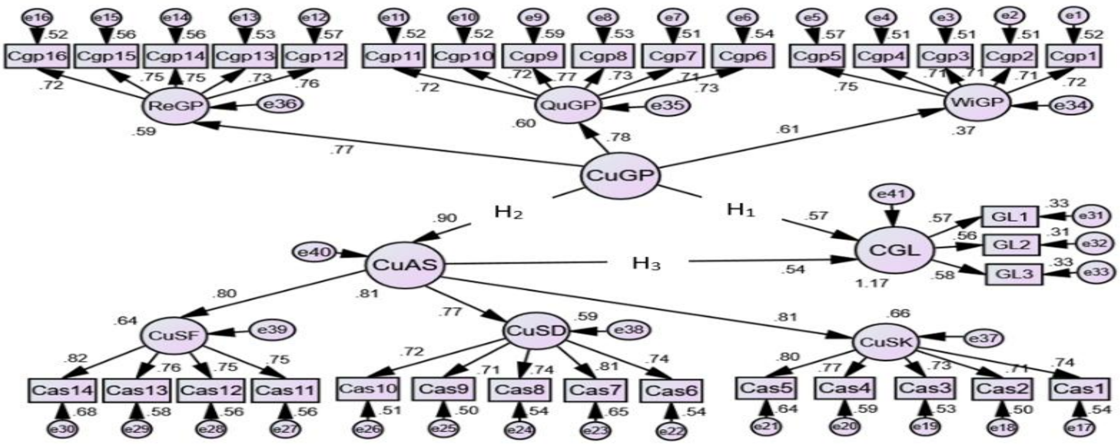


**Figure 3: Structural model of perception-attitude-loyalty**

Model-fitting of the structural model is acceptable as the key fit-indices are successfully meeting the cut-off criteria. Specifically, the values of IFI, TLI, & CFI (.911, .903, & .911) are surpassing the threshold of .9 (Hu & Bentler, 1998); The CMIN/DF value (2.420) is below 3 (Schreiber et al., 2006); the SRMR value (.0499) is below .08, and the RMSEA value (.056) is below .06 (Hu & Bentler, 1999). Thus, three major hypotheses ($H_1$, $H_2$, & $H_3$) are tested successfully by the above structural model. The results are detailed in Table 3. The standardized regression weights depicted in the model (figure 3) justifies their significant effects on the hypotheses.

**Table 3: Major hypotheses testing through structural model and results**

| Hypotheses and their position in the structural model | Β | S.E. | 't' | Results |
|---|---|---|---|---|
| Customers' green perception has a positive effect on their green-loyalty. ($H_1$: CGL◄ – – CuGP) | .572 | .243 | 2.639* | Supported |
| Customers' green perception has a positive effect on their attitude towards sustainability. ($H_2$: CuAS ◄ – – CuGP) | .900 | .105 | 10.217** | Supported |
| Customers' attitude towards sustainability has a positive effect on their green-loyalty. ($H_3$: CGL ◄ – – CuAS) | .539 | .197 | 2.571* | Supported |

CuGP: Customers' green perception; CuAS: Customers' attitude towards sustainability; CGL: Customers' green-loyalty β-Standardised Regression Weight; 't'-Critical Ratio; S.E.- Standard Error; **Significant at 1% level of significance; *Significant at 5% level of significance.

Source: Authors' compilation.

Table-3 shows that three major hypotheses are supported. That means customers' green perception exerts significant positive effects (approximately 57% & 90%) on their green-loyalty and on their attitude towards sustainability. Additionally, attitude towards sustainability also has a significant positive (nearly 54%) effect on their green-loyalty. Three hypotheses being supported is logically underpinning the 4$^{th}$ hypothesis ($H_4$) that the indirect effect (through mediating effect of attitude towards sustainability) of green perception on green-loyalty is significant.

## 4.8. Moderation of Customers' Risk-Perception

The moderating effect of customers' risk-perception is tested through the model-59 of Hayes (2018) in Process-Macro of SPSS that also tests the hypothesis-5. The statistical and their inferences are refelected in table 4.

**Table 4: Testing of the moderation of customers' risk-perception (CRP) on the effect of CuGP on CGL through CuAS**

| Interactions with CRP | Coefficient | SE | 't' | P | LLCI | ULCI | Inference |
|---|---|---|---|---|---|---|---|
| Int_1 with the outcome variable as CuAS | -.0973 | .0719 | -1.3531 | .1767 | -.2386 | .0440 | Moderation effect is not significant |
| Int_1 with the outcome variable as CGL | .0829 | .0671 | 1.2354 | .2173 | -.0490 | .2148 | |
| Int_2 with the outcome variable as CGL | .0286 | .0417 | .6861 | .4930 | -.0533 | .1105 | |

SE- Standard Error; LLCI- Lower-Level Confidence Interval; ULCI- Upper-Level Confidence Interval; CuGP- Customers' green perception; CuAS- Customers' attitude towards sustainability; CGL- Customers' green-loyalty; Int_1 = CuGP X CRP; Int_2 = CuAS X CRP

Level for all confidence intervals- 95.000, Number of bootstrap samples- 5000

Source: Authors' compilation.

Table 4 reflects that the 't' statistics are not significant ($p > 0.05$) in all cases, even at the 5% significance level. Further, 'zero' can appear between lower-level confidence interval (LLCI) and upper-level confidence interval (ULCI) as all LLCI are negative and ULCI are positive. Therefore, customers' risk-perception (CRP) is not moderating the effects of customers' green perception on their attitude and green-loyalty. Also, CRP is not moderating the effect of customers' attitude towards sustainability on their green-loyalty.

## 5. Findings

By confirming customers' green perception with 3 constructs, 'willingness to pay more for green products', 'quality of green products', and 'recycling nature of green products'. Among these, product quality and recycling characteristics emerged as more influential in shaping a favorable green perception. Similarly, the study evaluated customer attitudes towards sustainability based on 'sustainability decision', 'sustainability knowledge', and 'sustainability feeling'. It found that sustainability knowledge and feelings play a stronger role in fostering positive attitudes toward sustainability.

Customers' green perception & attitude towards sustainability both positively and significantly build their green-loyalty, with green perception exerting a stronger influence than attitude alone. But the combined effect is more powerful (significantly more positive effect) for green-loyalty as green perception has significantly more effect on attitude towards sustainability. These findings highlight the strategic importance of aligning customers' green perceptions with their sustainability-related attitudes to maximize the competitive advantages of green marketing efforts.

Customers' attitude towards sustainability significantly mediates the effect of green-perception on green-loyalty in the context of green marketing. So, customers' selectivity of receiving the stimuli (products with green features) can be made by restricting their attitude (Assael, 1995) towards sustainability in the way of their loyalty towards those brands of marketers that carry green features (green-loyalty) to take competitive advantage.

As customers' risk-perception is not moderating the impact of perception on green-loyalty and on their attitude towards sustainability, perception-attitude parity can enjoy a royal status or can play undisputed role in driving the customers towards those brands that carry green features. The insignificance of risk perception as a moderator may stem from the evolving consumer mindset in green markets. As sustainability becomes a normative expectation, consumers increasingly rely on trust, value alignment, and social proof rather than risk evaluation. These dynamics suggest that risk perception may not exert a strong conditional influence on the relationship between customers' green perception, attitudes towards sustainability, and their loyalty. Thus, marketers should not be muddled with various complex strategies or plan, rather should rely on simple and plain strategic plans to drive the customers towards green-products.

## 6. Conclusion

The strategic orientation of customer loyalty, perception, attitude and risk-perception in the background of greenness and sustainability reveals vital implications for businesses and public planners. The present study is accomplished focusing on the antecedents of customers' green-perception and attitude towards sustainability that forms their green-loyalty, with the mediation of customers' attitude towards sustainability and moderation of risk-perception. These facts are the key contributions of this study. This research-work finds both the customers' perception and attitude to be influencing their green-loyalty with the moderated mediation approach. However, risk-perception did not have the anticipated impact, which suggests that it may hold less predictive weight for green loyalty in similar consumer segments.

To truly harness the plausible benefits of green-loyalty, marketers and policymakers must act on these findings. Marketers should focus on enhancing customers' green perception and positive attitude through transparent communication, eco-friendly offerings, and credible certifications. Since risk perception has little impact, strategies should emphasize sustainability benefits and brand authenticity to foster stronger green loyalty. Therefore, by addressing customers' perceptions & cultivating positive attitudes towards sustainability, a path can be paved for a better tomorrow. Furthermore, the study contributes to academic literature by extending sustainability research through the lens of green consumer behavior, highlighting perceptual, attitudinal and loyalty dynamics within emerging market contexts.

The geographical scope of this study is confined to a single state in India, which may influence the generalizability of the findings. Future investigations could expand the research area to encompass broader regional or national contexts, thereby enhancing the applicability of the results. While we suggest geographic expansion, we also acknowledge that perceptions & attitude in green context vary across cultures and regions. The cross-sectional design limits temporal insights, and future research could adopt longitudinal methods, mixed approaches, and more diverse consumer segments to enhance cultural relevance and generalisability. Along with this the method bias and measurement constraints may also affect the robustness and generalisability of the findings. Further, our sample showed demographic imbalances, with 60% of respondents under 30 and 54% being private employees, while only 5% were students. Although these groups are central to eco-conscious markets, the skew may limit generalisability across age and occupational segments. Future studies should consider more diverse samples to validate and broaden these insights. The current study considers only three constructs each for the customers' green perception and their attitude towards sustainability, but similar future studies can incorporate additional relevant constructs to explore new ways to build strong customer-loyalty towards products with green features.

The marketers starting from designing to delivering the product or services, must give maximum priority to green features through clearly communicating eco-benefits through product labeling and aligning promotional strategies with values-driven messaging, by which green perception will be developed that ultimately develop the positive attitude towards sustainability.

The marketers, through various promotional campaigns, awareness campaigns, and/or by educating the customers, must try to connect the target customers to the environment-friendly objects that are valued most by customers. As a result, the attitude towards sustainability can be emerged & enhanced.

Thereby, green perception can be connected to attitude towards sustainability to gain strategic advantages. Further, the policymakers should incentivize green product adoption through targeted subsidies and awareness campaigns, especially among younger and private-sector consumers.

Both green perception and attitude toward sustainability simultaneously influence customers' green-loyalty. So, the strategies or plans, we are suggesting are integrated in nature. Therefore, management practitioners should revisit their understanding that marketing strategies are not only meant for commercial purposes like profit and revenue but also can be connected to social restructuring through the social wellbeing of the customers.

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