Volume 3 • Issue 1
March 2025

MDI MURSHIDABAD Management Development Institute

mjmrp.mdim.ac.in
e-ISSN: 2583-8768

MDIM JOURNAL OF MANAGEMENT REVIEW AND PRACTICE

e-ISSN: 2583-8768

MDIM Journal of Management Review and Practice is published biannually in March and September by Management Development Institute Murshidabad (MDIM).

MDIM Journal of Management Review and Practice is hosted on our web-based online submission and peer review system. Please read the manuscript submission guidelines on the journal website, and then visit https://peerreview.sagepub.com/mbr to login and submit your article online. Manuscripts should be prepared in accordance with the 7th edition of the *Publication Manual of the American Psychological Association*.

Annual Subscription: Individual rate (print only) ₹1,720; institutional rate (print only) ₹2,790. For orders from Pakistan, Bangladesh, Sri Lanka and Maldives, SAARC rates apply: individuals $35; institutional rate $50. Prices include postage. Print subscriptions are available for institutions at a discounted rate. For subscriptions, please write to: customerservicejournals@sagepub.in

Change of Address: Four weeks' advance notice must be given when notifying change of address. Please send the old address label to ensure proper identification. Please specify the name of the journal and send change of address notification to customerservicejournals@sagepub.in

Printed and published by Mr. Debasish Gupta on behalf of Management Development Institute Murshidabad, Sakim-Katnai, Kulori, P.O. - Uttar Ramna, P.S. - Raghunathganj, Dist. Murshidabad, West Bengal, India. Printed at Sai Printo Pack Pvt Ltd, A 102/4 Phase II, Okhla Industrial Area, New Delhi, Delhi 110020.

Editor: Dr. Souvik Banerjee

MDI MURSHIDABAD Management Development Institute

About the Journal

MDIM Journal of Management Review and Practice is published by Management Development Institute Murshidabad. The journal started publishing in 2023 in English Language. The journal aims to create and advance knowledge in the field of management sciences and its allied disciplines. High quality research papers, case studies, opinion pieces and book reviews are published in *MDIM Journal of Management Review and Practice*.

Through thought leadership, the journal fosters a knowledge ecosystem that enriches the existing body of knowledge.

MDIM Journal of Management Review and Practice is published twice a year, in March and September. The journal publishes research works that are thought provoking. The most recent developments in the following fields have been covered in recent years. Thought leaders, researchers, academicians as well as corporate professionals publish their scholarly work through this outlet.

The indicative list of areas on which research work is published in this journal are as follows:

- General Management
- Finance & Accounting
- Economics
- Information Technology
- Marketing
- Human Resource Management
- Ethics
- Organization Behaviour
- Operation and Strategic Management
- Public Policies and Governance

The journal has provided a forum for debate and a platform for exchange of ideas from a diverse range of scholarly perspectives in order to promote research with quantitative, qualitative as well theoretical underpinnings on issues confronting the world as a whole in general and business world in particular.

The main features (paper types) of the journal are as follows:

- Applied and Normative Research
- Review Articles
- Case Studies
- Book Reviews

MDI MURSHIDABAD Management Development Institute

Aims and Scope

MDIM Journal of Management Review and Practice, a humble initiative of Management Development Institute Murshidabad, strives and fosters to propel research in the arena of business and management sciences by providing evidence-based research papers of highest quality for academicians, researchers, managers and policy makers. The journal endeavors to create influence on corporate and academia think tanks. It aspires to provide a platform for discussions and cross-pollinations of ideas across wide spectrum of scholarly perspectives to garner theoretical, empirical and comparative research on ongoing and probable problems in the business world.

MDIM Journal of Management Review and Practice
Volume 3 Issue 1 March 2025

Contents

Article

Societal Impact of Machine Learning on Human Emotions

MDIM Journal of Management Review and Practice
3(1) 7–17, 2025

DOI: 10.1177/mjmrp.241284450
mbr.mjmrp.mdim.ac.in

Abhijit Pandit[1] and Trinankur Dey[2]

Abstract

Modern networking conversations generate annotated metadata, necessitating a method for synthesizing insights from statistics. Emotion detection is crucial for practical conversations, distinguishing joy, grief, and wrath. Corpora are becoming the standard for human–machine interaction, aiming to make interactions feel natural and real. A paradigm that identifies debates and customer views can provide a human touch to these interactions. Researchers developed a machine learning framework for assessing emotions in English phrases, utilizing Long Short Term Memory perspective and real-time emotion recognition in idiomatic speech. Emotion recognition rule is created using ontologies like Word Net and Concept Net, Naive Bayes, and Random Forest. Real-time analysis of written words and facial expressions significantly outperforms current algorithms and commandment classifiers in identifying emotional states.

Keywords

Feelings, detailed statistics, data mining, machine learning

Introduction

Social Impact

Emotion recognition challenges humans to comprehend emotions, requiring advanced machine learning techniques, and comprehensive data for robots to effectively respond. Emotion recognition challenges individuals' perception and understanding, but humans can identify and express emotions (Zahra et al., 2009).

[1]Management Development Institute Murshidabad, Kolkata, West Bengal, India
[2]Faculty of Management and Commerce, The ICFAI University Tripura, Kamalghat, Tripura, India

Corresponding author:
Abhijit Pandit, Management Development Institute Murshidabad, Kolkata, West Bengal 742235, India.
E-mail: abhijitpandit1978@gmail.com

To effectively respond to emotional cues, robots require statistical data and advanced machine learning techniques (Cohn & Katz, 1998). Advanced monitoring systems identify users' thoughts and emotions through conversational formats (Liyanage et al., 2000). Wearable biosensors analyse emotions using web browsers and calendars. The evolution of monitoring systems has paved the way for the identification of users' emotions across diverse communication formats, such as chat messages and social media interactions. While wearable devices can capture biomedical data, their practicality for day-to-day use is limited. In this context, the integration of soft biosensors into web browsers emerges as a novel approach, employing analyses of tools like calendars and social networks to infer users' emotional states.

Text-based emotion recognition applications include detecting adverse emotions in email communications, improving query retrieval, and using emotional models like hourglass and Ekman's categories. Understanding emotional keywords and contextual placement in text is essential for emotion detection (Kao et al., 2009). Practical applications of text-based emotion recognition extend to areas like identifying negative emotions in emails to safeguard employees' well-being. Employing a search engine to categorize notes based on emotional states holds the potential to elevate user experiences and enhance the retrieval of relevant queries. Emotion identification systems rely on established models like the hourglass model and Ekman's emotion categories. The precise comprehension of emotional keywords and their contextual positioning within text becomes pivotal for achieving accurate emotion detection. Even emotion recognition encompasses the analysis of facial expressions and textual content. Emotion recognition involves analysing facial expressions and textual content. Advances in facial expression detection and comprehension enable automated systems to accurately perceive and respond to human emotions (Calvo & D'Mello, 2010). Leveraging computer vision and artificial intelligence techniques, algorithms, and statistical methods are employed to recognize facial expressions.

Figure 1 score is crucial in machine learning for assessing classification models' performance in imbalanced datasets. This study aims to identify emotions from neutral to intense sentiments, contributing to emotion recognition and societal implications.

Emotion classification uses keyword-based, machine learning, and hybrid methods to improve accuracy and impact society by systematically categorizing emotional keywords using tools like WordNet-Affect.

Nonetheless, the exclusive reliance on keywords encounters drawbacks tied to context and ambiguity, which have implications for understanding emotions in various contexts. Machine learning strategies, on the other hand, leverage trained models to achieve precise emotion recognition, with a particular emphasis on understanding the context within sentences.

The integration of semantic labels and sentence features presents innovative yet intricate techniques with potential social implications. Techniques such as mutual action histograms offer promise in identifying heightened emotional states

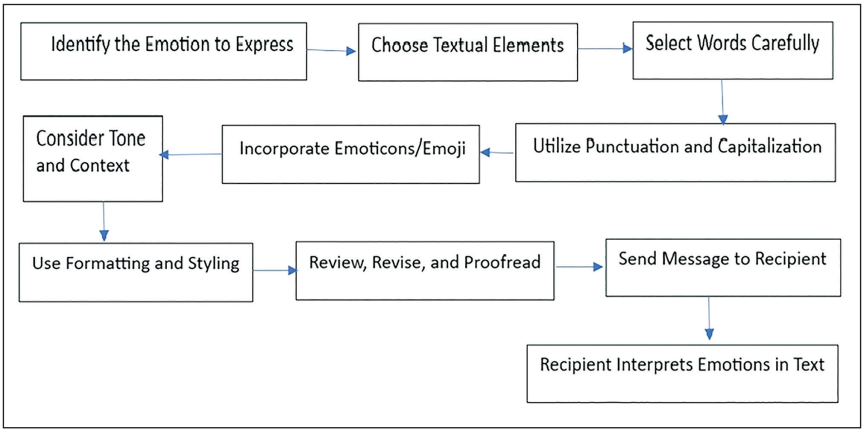


Figure 1. Workflow Diagrams for Expressing Emotions via Text.

in text, which could impact how emotions are interpreted and understood in online conversations.

Hybrid approaches combining Support Vector Machines (SVM), Naive Bayesian, and Max Entropy introduce opportunities to elevate the accuracy of emotion classification, which in turn could benefit applications across social interactions. Hierarchical taxonomy systems and rule-based morphological systems contribute to refining the accuracy of these methods, potentially influencing how emotions are detected and interpreted in various forms of communication.

Review of Literature

The challenges inherent in emotion recognition prompt a diverse exploration of methods, a pursuit that can contribute to understanding and improving emotional interpretation in digital communication. The incorporation of recurrent neural networks and distributional semantic models introduces potential avenues to further advance emotion recognition techniques, with possible implications for how emotions are comprehended and engaged with across various societal contexts.

Bibliometric Coupling

Bibliometric coupling is a technique employed in bibliometrics and scientometrics to build a relationship between scientific articles based on the number of references they have in common. This methodology facilitates the identification and visualization of the cognitive framework of study domains, groups of interconnected documents, and developing patterns in scientific literature.

Coupling Strength refers to the degree of interdependence or connection between two or more entities. It measures the extent to which changes in one entity affect or influence the behavior of another entity. The degree of coupling between two papers is measured by the number of references they share. A higher coupling strength implies a stronger correlation between the texts, indicating that they are operating within the same scientific topic or subfield.

Visualization of a Network

Documents are depicted as nodes inside a network. The edges, which are lines connecting the nodes, show the degree of connectivity between them. The thickness of the edges can indicate the level of coupling strength, with thicker lines representing stronger connections.

Groupings

Nodes (documents) that have a strong correlation tend to group together in clusters.

Every cluster has the ability to represent a distinct topic, theme, or study area within the wider field. Clusters can be differentiated by utilizing various colors.

Image Analysis

The graphic depicts a network of papers that is formed by bibliometric coupling. Below is a comprehensive analysis of the various elements: Nodes (sometimes known as bubbles):

The magnitude of the bubble frequently signifies the number of citations that document has garnered, with larger bubbles denoting articles that have earned a greater number of citations.

Designations

The labels on the bubbles commonly display the author(s) and the year of publication. For example, the term "chou (2020)" denotes a scholarly article authored by Chou and published in the year 2020.

Color Spectrum

Distinct hues are employed to indicate separate clusters. For instance, the green bubbles could symbolize a distinct field of research, while the blue bubbles indicate a different field. Edges, often known as lines, are one-dimensional geometric figures that extend infinitely in both directions.

The lines connecting the bubbles indicate bibliometric connection. The quantity and width of these lines signify the intensity of the relationship. Increased line density or increased line thickness between two bubbles indicates a greater number of shared references. Research significance is in its ability to identify and analyse current trends in the field. Bibliometric coupling enables academics to

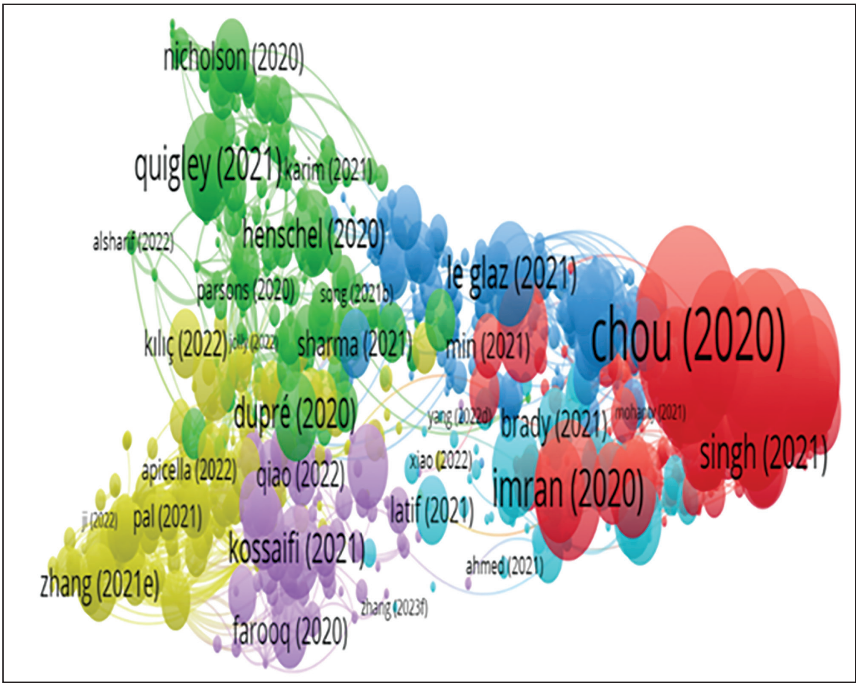


Figure 2. Bibliometric Coupling was Performed on Available Literature with the Help of Dimensions and VOSviewer.

Source: Created with the help of Dimensions and VOSviewer.

discern prevailing patterns and popular subjects within a particular domain. Through the analysis of clusters (Figure 2), one can discern the predominant focus of attention and identify developing areas of interest.

Knowledge Domain Mapping

It offers a graphical depiction of the interconnections between various scientific subjects. Researchers are able to gain insight into how their study aligns with the wider scope of their area.

Cooperation and Establishment of Professional Connections

This approach might additionally emphasize possible partners by displaying the researchers who are engaged in comparable subjects.

Strategic Planning

Institutions and funding bodies can utilize bibliometric coupling to pinpoint crucial areas for investment and support. It aids in making well-informed decisions regarding the prioritization of research fields.

Analysis of the Image: Prominent Clusters

The red cluster, featuring distinguished writers such as Chou et al. (2020) and Singh et al. (2021), signifies a firmly established field of research with notable interrelationships. Smaller clusters or isolated nodes may indicate nascent areas of research that are currently in the process of development. Chou et al. (2020) is represented by larger bubbles, indicating that these articles have received a high number of citations, reflecting their significant influence within their respective study field. Interdisciplinary study or the convergence of multiple fields is indicated by the connection of clusters of different colors in specific locations. Through the examination of bibliometric coupling, researchers can acquire a more profound comprehension of the organization and fluctuations of scientific knowledge, enabling them to navigate the extensive body of literature with greater efficiency.

The surge in sentiment analysis's popularity and its impact on human–computer interaction has spurred researchers to confront the issue. Cognitive neuroscience, delving into the brain–mind connection, underscores the insufficiency of solely relying on logic for decision-making.

In response to this challenge, researchers have embraced sophisticated methods such as bidirectional long short-term memory for training models. The refinement of the initial training phase and enhancement of model accuracy are achieved through hyperparameter tuning. Additionally, preprocessing procedures play a role in augmenting model performance.

Methodology

The researchers utilized libraries for text and facial expression analysis, imported classifiers, and performed algorithm evaluation using test train split. Random Forest and Naive Bayes algorithms were implemented, and a classification report was obtained. The neural network model processed input images for real-time emotion prediction.

The output of this code, depicted in Figure 3, demonstrates the prediction of human emotions utilising a deep learning model in Python.

SVM is a supervised machine-learning algorithm effective in binary and multiclass classification tasks. It finds an optimal hyperplane to separate data points of different classes in a multidimensional space, with support vectors playing a vital role. SVM uses the kernel trick for nonlinear data and allows for soft margin classification. It has advantages in handling high-dimensional data and robustness against overfitting. However, SVM can be computationally expensive for large datasets, and tuning the kernel and penalty parameter C is essential for optimal performance. Overall, SVM is widely used in machine learning for binary classification tasks.

Results and Implications

To display human emotions in pictures using Python, you can use facial expression recognition libraries and tools. One popular library for this purpose is OpenCV,

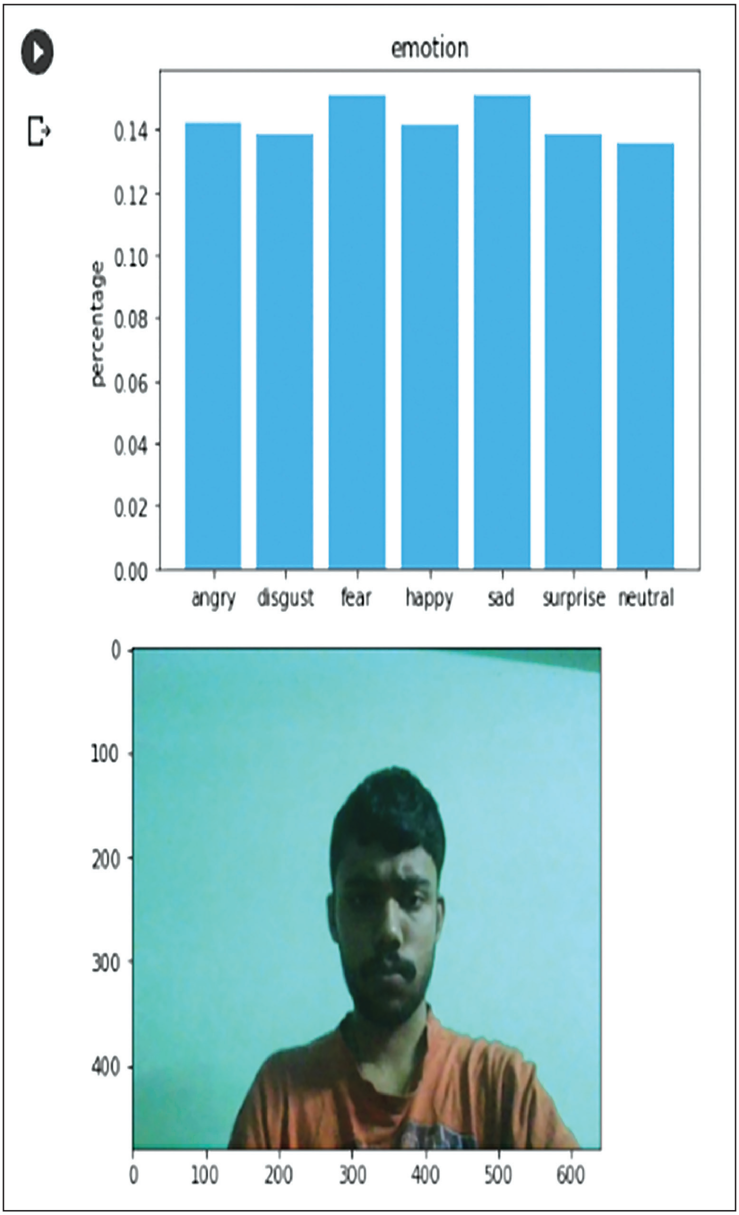


Figure 3. Prediction of Human Emotions Using Deep Learning Model and Python.

which provides functionalities for face detection and facial expression recognition. Additionally, you can use pretrained deep learning models for emotion recognition, such as those available in the TensorFlow or PyTorch ecosystems. Here's a simple example using OpenCV for facial expression recognition:

```
import numpy as np
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Step 1: Load and preprocess the dataset
# Assuming you have features (X) and corresponding emotion labels (y)

# Step 2: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_
state = 42)

# Step 3: Choose and train the machine learning model (e.g., SVM)
model = SVC(kernel = 'linear')
model.fit(X_train, y_train)

pip install opencv-python
pip install numpy
import cv2
import numpy as np

# Load pre-trained Haar Cascade classifier for face detection
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + 'haarcascade_
frontalface_default.xml')

# Load pre-trained deep learning model for emotion recognition
emotion_model = cv2.dnn.readNetFromTensorflow("path/to/your/emotion_
model.pb")

# Define emotion labels
emotion_labels = {0: 'Angry', 1: 'Disgust', 2: 'Fear', 3: 'Happy', 4: 'Neutral',
5: 'Sad', 6: 'Surprise'}

# Load the input image
image_path = "path/to/your/image.jpg"
image = cv2.imread(image_path)

# Convert the image to grayscale
gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Detect faces in the image
faces = face_cascade.detectMultiScale(gray_image, scaleFactor = 1.1,
minNeighbors = 5, minSize = (30, 30))

# Process each detected face
for (x, y, w, h) in faces:
face_roi = gray_image[y:y + h, x:x + w]
face_roi = cv2.resize(face_roi, (48, 48))
face_roi = face_roi.astype("float") / 255.0
face_roi = np.expand_dims(face_roi, axis = 0)
face_roi = np.expand_dims(face_roi, axis = −1)

# Predict the emotion
emotion_preds = emotion_model.predict(face_roi)[0]
emotion_label = emotion_labels[np.argmax(emotion_preds)]
```

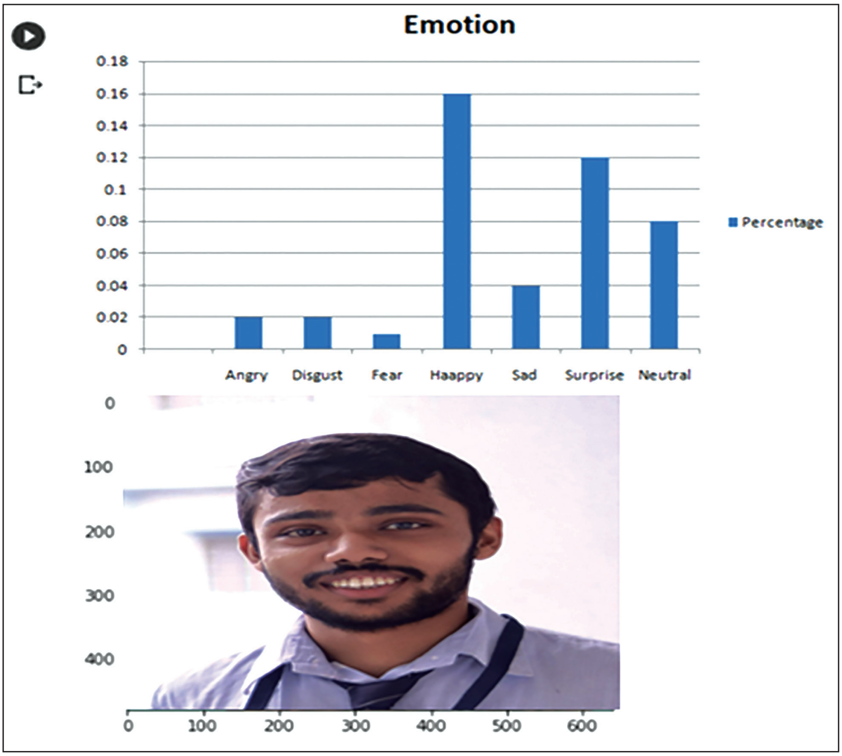


Figure 4. Prediction ii of Human Emotions Using Deep Learning Model and Python.

```
# Draw a rectangle around the face and display the emotion label
cv2. rectangle(image, (x, y), (x + w, y + h), (0, 255, 0), 2)
cv2. put Text (image, emotion_label, (x, y − 10), cv2. FONT_HERSHEY_
SIMPLEX, 0.8, (0, 255, 0), 2)
```

In this code, one needs to replace "path/to/your/emotion_model.pb" with the actual path to pretrained deep learning model for emotion recognition. The model should be trained to recognize emotions like Angry, Disgust, Fear, Happy, Neutral, Sad, and Surprise.

Figure 4 illustrates the model's capacity to forecast human emotions, highlighting its practical utility.

To maximize the positive impact of machine learning on human emotions, human-cantered design, ethical considerations, and inclusivity must be prioritized, involving collaboration between technologists, healthcare professionals, and users themselves.

Conclusion

In summary, there are a lot of potential and obstacles in the subject of emotion recognition when it comes to teaching robots to understand and react to human emotions. Robust datasets and sophisticated machine-learning algorithms are needed for this. Humans are naturally able to recognize and communicate their emotions (Zahra et al., 2009); however, robots find it difficult to effectively understand these signs and must instead rely on statistical data and complex algorithms (Cohn & Katz, 1998). According to De Silva and Ng (2000), the development of monitoring systems has made room for novel methods of identifying emotions, such as the combination of web-based resources with wearable biosensors. However, wearable technology is still not very useful for everyday tasks, which makes soft biosensors incorporated into online settings a viable substitute for inferring. Text-based emotion identification has several real-world uses, such as enhancing query retrieval systems and identifying negative emotions in emails to protect worker welfare. Emotional keywords and their contextual location must be understood in order to accurately identify emotions in text. This may be done by using models such as the hourglass and Ekman's emotion categories (Kao et al., 2009). Artificial intelligence and computer vision developments have expanded automated systems' capacity to interpret text and facial expressions (Calvo & D'Mello, 2010). Such systems use difficult algorithms, as well as statistical techniques; thus, boosting the identification of emotions. Emotion recognition technologies, facial expression analysis, as well as text analysis, provide new opportunities in increasing human–computer interaction and understanding the dynamics of emotions that engulf various communication channels. OpenCV and TensorFlow or PyTorch libraries allow demonstrating their practical usability in the case of facial expression detection and deep learning models, which affect social interaction and the field of artificial intelligence.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, or publication of this article.

Funding

The authors received no financial support for the research, authorship, or publication of this article.

ORCID iDs

Abhijit Pandit https://orcid.org/0000-0003-2122-3468
Trinankur Dey https://orcid.org/0000-0002-1119-2496

References

Calvo, R. A., & D'Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. https://doi.org/10.1109/t-affc.2010.1

Chou, S. T., Lee, Z. J., Lee, C. Y., Ma, W. P., Ye, F., & Chen, Z. (2020). A hybrid system for imbalanced data mining. *Microsystem Technologies*, *26*(9), 3043–3047.

Cohn, J. F., & Katz, G. S. (1998). Bimodal expression of emotion by face and voice. In *Proceedings of the sixth ACM international conference on Multimedia: Face/*

gesture recognition and their applications (pp. 41–44). Association for Computing Machinery. https://doi.org/10.1145/306668.306683

De Silva, L., & Ng, N. P.C. (2002). Bimodal emotion recognition. In *Proceedings fourth IEEE international conference on automatic face and gesture recognition*. IEEE. https://doi.org/10.1109/afgr.2000.840655

Kao, E. C. C., Liu, C. C., Yang, T. H., Hsieh, C. T., & Soo, V. W. (2009). Towards text-based emotion detection a survey and possible improvements. In *Proceedings of the 2009 international conference on information management and engineering*. IEEE. https://doi.org/10.1109/icime.2009.113.

Khalili, Z., & Moradi, M. H. (2009). Emotion recognition system using brain and peripheral signals: Using correlation dimension to improve the results of EEG. In *Proceeding of the 2009 international joint conference on neural networks* (pp. 1920–1924). IEEE.

Liyanage, L., Elhag, T., Ballal, T., & Li, Q. (2000). Knowledge communication and translation – A knowledge transfer model. *Journal of Information & Knowledge Management, 8*(1), 31–42.

Singh, J., Aggarwal, S., & Verma, A. (2021). Application based categorization of datasets for implementing data mining techniques. In *Proceedings of the 2021 2nd global conference for advancement in technology (GCAT)* (pp. 1–7). IEEE.

Zahra, S. A., Gedajlovic, E., Neubaum, D. O., & Shulman, J. M. (2009). A typology of social entrepreneurs: Motives, search processes, and ethical challenges. *Journal of Business Venturing, 24*(5), 519–532.

Article

MDIM Journal of Management
Review and Practice
3(1) 18–36, 2025

DOI: 10.1177/mjmrp.241290938
mbr.mjmrp.mdim.ac.in

Understanding the Influence of Subjective Financial Literacy on the Investment Decisions of Individual Investors in India

Zafar Alam[1], Lamaan Sami[1], Mohd Aman[1] and Fahad[1]

Abstract

The present work examines the association between subjective financial literacy, self-reported by Indian individual investors and the factors that affect their investment decisions concerning fundamental and technical analysis. A structured questionnaire was employed using a purposive sampling procedure to collect the requisite data from individual investors on their demographic profiles, perceived financial literacy and determinants of investment decisions. For developing the measurement model and testing the research hypotheses, Partial Least Squares Structural Equation Modeling (PLS-SEM) was taken into consideration. The result showed that conceptual knowledge, accounting information, technical knowledge and market information are positively associated with the investors' investment decisions. Furthermore, it highlighted the role of subjective financial literacy in significantly impacting investors' investment decisions. This study is the first of its kind because previous studies completely ignored the need to assess the perceived financial literacy of investors and its association with the factors determining their investment decisions. Based on the study's findings, fruitful suggestions are provided to various stakeholders.

Keywords

Behavioural finance, financial planning, financial market, investment analysis, customer knowledge

[1]Department of Commerce, Aligarh Muslim University, Aligarh, Uttar Pradesh, India

Corresponding author:
Fahad, Department of Commerce, Aligarh Muslim University, Aligarh, Uttar Pradesh 202001, India.
E-mail: ahmadalig300@gmail.com

Introduction

The expanding body of literature on financial literacy (FL) has established that FL is a crucial aspect of the financial system. Consequently, FL is gaining traction among governments, regulators, policymakers and several other organisations across the economies with a broader vision to educate the people financially and thereby help them optimise their financial resources (Suresh, 2024). The necessity of enhancing FL has grown due to the creation of innovative financial products, the intricacy of the financial markets and the complexity of using financial technology (Hassan Al-Tamimi & Anood Bin Kalli, 2009). Handling one's finances is now more difficult than ever because of the economy's changing environment and the difficulty in making financial decisions (Jariwala, 2015). Additionally, income and wealth inequality across economies has gained the attention of economic and political forums worldwide, and FL plays a vital role in explaining wealth inequality (Lusardi et al., 2017).

Due to the emergence of the COVID-19 pandemic, the participation of individual investors in the stock market increased significantly in 2020 and 2021 across several economies. Consequently, individual investors constituted a significant portion of the trading value. This could be attributed to their increased interest while staying or working from home during the COVID-19 pandemic shift in investments towards high-yielding securities due to a decline in real interest rates in a climate of easing monetary policy and rising inflation (Adil et al., 2022). Given these developments, the need for financial education is paramount. Moreover, several studies from different nations prove that the FL of an individual influences their financial behaviour and investment decision-making (Bernheim, 1998; Cole et al., 2011). FL is a significant factor in investors' participation in the stock market and investment decisions. Financially educated individuals can make better investment decisions, secure their financial future and fulfil their objectives, thereby improving their economic stability (Amari & Anis, 2021; Hassan Al-Tamimi & Anood Bin Kalli, 2009; Van Rooij et al., 2011).

Decision-making is commonly defined as selecting a particular option from various available options. It is a task that follows after thoroughly assessing all the options. According to Karlsson et al. (2004), people make personal economic decisions regularly, and even though these decisions are essential for daily life, they may be challenging. Many researchers have extensively recognised the relevance of analysing consumers' decisions (Jariwala, 2015).

The theories of standard finance assume that decision-makers are rational and capable of making the most of all the information at their disposal. However, behavioural finance theories hold that individuals tend to make irrational decisions. These theories challenge the assumption of absolute rationality. The psychological process that describes the irrational behaviour of investors is representativeness, heuristics, conservatism, overconfidence and self-attribution (Jariwala, 2015).

Several past and current studies examine the factors that affect individual investors' decision-making (Ansari et al., 2023; Baker & Haslem, 1974; Chandra & Kumar, 2011; Hassan Al-Tamimi & Anood Bin Kalli, 2009; Merikas et al., 2004; Prasad et al., 2021). Although the measurement of FL has gained much consideration, researchers have paid less attention to investigating the empirical connection between perceived FL and determinants of investment decisions, warranting further studies to explore how individual investors' FL affects their investment decisions, especially in the developing economy like India (Chawla et al., 2022). Therefore, this study is carried out to assess the perceptions of individual investors regarding their FL and its influence on their investment decisions.

The second section provides a detailed and thorough analysis of the literature on FL and determinants of investment decisions, as well as the method and description of the scales employed to evaluate the level of FL. The third section describes the research methodology used to achieve the stated objective of this study. The fourth section discusses the results and findings. Finally, the fifth section discusses the results, implications, limitations and future research scopes.

Review of Literature and Hypothesis Development

Financial Literacy

Noctor et al. (1992) stated, 'financial literacy is the financial knowledge that leads to informed decision-making'. Here, it can be seen that this definition has two aspects. The first aspect relates to the financial knowledge that results from financial education programmes, and the other is the capability to use the acquired accounting information effectively to make better investment decisions (Rai et al., 2019). According to Adil et al. (2022), '*financial literacy is creating awareness and understanding of the mechanisms of financial markets to choose financial products, manage risks, and optimise returns'.* Lusardi and Mitchell's (2014) definition goes beyond the financial knowledge taken into account by earlier definitions. They defined FL as 'the ability of economic information analysis and informed financial decision-making'. According to Lusardi and Mitchell (2014), people are deemed financially illiterate if they possess financial information but cannot use it effectively to make better financial decisions.

OECD (2005) presents the most extensive definition of FL as 'a combination of awareness, knowledge, skill, attitude, and behaviour necessary to make sound financial decisions and ultimately achieve individual financial well-being'. The above definition covers several dimensions of FL, including financial knowledge, its comprehension, skills acquired and application of those skills, perceived knowledge (confidence to use it) and optimum decision-making. According to French and Mckillop (2016), the OECD's definition is more comprehensive and encompasses all aspects of FL.

Lusardi and Mitchell (2007a) designed two modules to measure two different levels of FL, that is, basic FL and advanced FL. The first module is designed to assess the participant's basic FL and consists of five questions relating to the following topics: (a) numeracy, (b) the concept of compound interest, (c) inflation, (d) the idea of the time value of money and (e) money illusion. The second list of items aims to assess advanced FL. It includes themes like the distinction between bonds and stocks, the workings of the stock market, the mechanisms of risk diversification and the link between bond price and interest rate. It is also important to note that academicians, researchers and institutions have broadly recognised and used these modules to measure FL. Similarly, OECD (2005) developed another set of questions to measure primary FL. They used seven distinct measuring items to determine the level of FL, including investment risk, compound interest and inflation. These measuring items align with the questions Lusardi and Mitchell (2007a) framed.

Furthermore, there are two measures by which the FL level of participants was assessed in the body of literature: objective and subjective measures (Allgood & Walstad, 2016; French & Mckillop, 2016). According to Ouachani et al. (2021), 'objective measures are based on items assessing the actual financial knowledge and skills of the respondents'. This measure is referred to as a knowledge-based performance test (French & Mckillop, 2016). Subjective FL refers to the degree to which individuals are financially confident and evaluate their self-reported or perceived financial knowledge (Bellofatto et al., 2018). Subjective FL has been evaluated in the literature by asking questions using a Likert scale to assess how respondents perceive their level of FL (Lusardi & Mitchell, 2007b). Several studies estimate the FL of investors using objective FL measures, which is not the case for subjective FL.

Therefore, this research is undertaken to assess the perception of individual investors regarding their FL and its impact on their investment decisions. Moreover, given the complexity of this concept, Moore (2003) proposes that FL cannot be measured directly, but proxies have to be used. Therefore, we use conceptual knowledge, accounting knowledge, technical knowledge and market information as proxies to measure FL.

Determinants of Investment Decision

Numerous studies have explored the factors that influence investors' decision-making. According to Baker and Haslem (1974), the critical elements for individual investors are the dividend, the expected return and the firm's financial condition. Merikas et al. (2004) found 26 factors that affect investors' decision-making in Greece. They classified these factors into categories: accounting information, subjective/personal, neutral information, advocate recommendation and personal financial needs. According to this study, accounting information, which includes the condition of financial statements, expected corporate earnings, expected dividends, the firm's position in the industry, affordable share price and past performance, was found to be the most critical element affecting investors' decisions.

According to Chandra and Kumar (2011), the investment decisions of retail investors are affected not merely by the recommendations of financial experts such as stock brokers, financial consultants and financial advisors but also by a range of other contextual factors. These factors include the company's market share, reputation, accounting, financial information, information available in the public domain by various media, advocate recommendations and personal financial requirements. In addition, they mentioned that while making an investment decision, people look at a company's market share, technical analysis and fundamentals (which include accounting and financial data). Hassan Al-Tamimi and Anood Bin Kalli (2009) explored 37 factors that influence the decisions made by individual investors in the United Arab Emirates. They discovered that the top four factors influencing investment decisions were religious motivations, firms' reputation, perceived ethical standards and the need for diversification, while the bottom four were rumours, family members' opinions, ease of borrowing money and recommendations from friends.

Subjective FL and Investment Decision

FL has been found to be a strong antecedent and predictor of determinants of investment decisions. A related work by Jariwala (2015) and Hassan Al-Tamimi and Anood Bin Kalli (2009) investigated the connection between objective FL and investment decisions among retail investors. The outcomes of their study demonstrated a strong association between FL and investment decisions. Also, investors' FL level greatly affects their capability to make investment decisions (Jariwala, 2015). Low FL negatively affects investment decisions, and investors make irrational investment decisions (Bucher-Koenen & Ziegelmeyer, 2011). Those with high levels of FL make their investment decisions better (Hilgert et al., 2003).

It is necessary to highlight that despite an enormous number of related work investigating the association between objective FL and investment decisions, there is a dearth of research exploring the association between subjective FL and the factors determining investment decisions (Mathew et al., 2024). This is because subjective FL assessment depends on individual investors' perception of their FL. It is assumed that respondents might get overconfident in the self-assessment of their accounting information and, as a result, overestimate how much they know. However, such subjective data could best capture the psychological factors influencing an individual's decision-making process (Bellofatto et al., 2018). Despite the increasing number of articles that depend on surveys to elicit investors' attributes, subjective data is still relatively infrequent in the financial literature (Glaser & Weber, 2007; Graham et al., 2009; Merkle & Weber, 2014).

To fill this void, the association between subjective FL and investors' behaviour was examined by Bellofatto et al. (2018). He discovered that investors who report more excellent financial knowledge appear to invest prudently. Prasad et al. (2021) conducted a similar study exploring the association between subjective FL and the determinants of investment decisions. This study classified the factors influencing FL into four categories: accounting information, market information, broad overview and technical knowledge. A significant positive association between subjective FL and determinants of investment decisions was found in this related work.

Therefore, this study also embraces this notion and develops the hypothesis that a significant and positive association exists between subjective FL and determinants of investment decisions. In our study, subjective FL encompasses four dimensions, that is, conceptual knowledge, accounting information, technical knowledge and market information. Moreover, Maditinos et al. (2007) found that investors were more concerned with fundamental and technical analysis while making investment decisions. Therefore, we considered fundamental and technical analysis as determinants of investment decisions.

This study develops the following four hypotheses based on the logical connection found in our discussion of the literature review, which gave evidence that subjective FL is an antecedent of investment decision determinants (see Figure 1).

H_1: Conceptual knowledge significantly impacts an individual's investment decision.
H_2: Accounting information significantly impacts an individual's investment decision.
H_3: Technical knowledge significantly impacts an individual's investment decision.
H_4: Market information significantly impacts an individual's investment decision.

Research Methodology

Research Instrument

The measuring items were adopted from several past related works for data collection from individual retail investors in India. A self-administered questionnaire comprised three sections: demographic profile, FL and factors determining

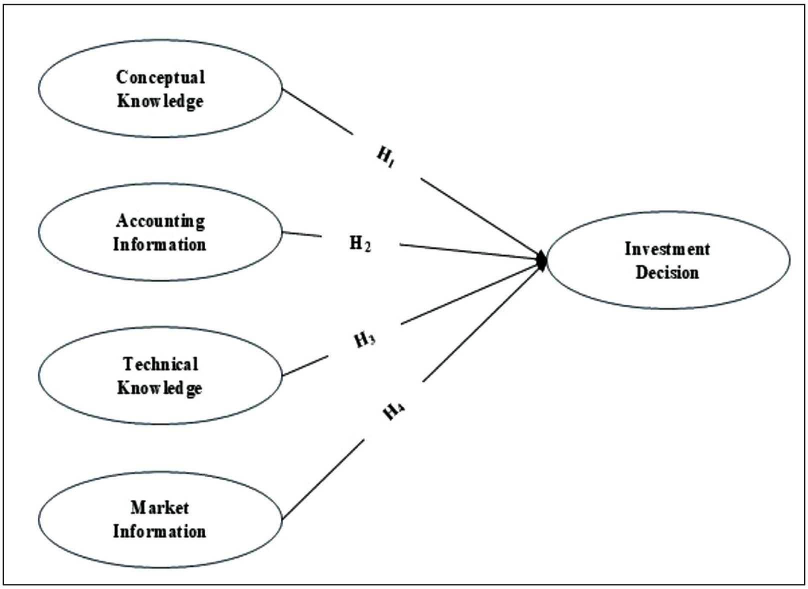


Figure 1. The Conceptual Model of the Study.

investment decisions. There were 26 items to collect study-related data, of which eight questions dealt with investment decisions, thirteen dealt with FL and five with demographic profiles. The questions based on FL were further categorised into factors where three items were related to conceptual knowledge, four were related to accounting information, three were related to technical knowledge, and three were related to market information. The items in the second and third sections of the questionnaire were graded on a Likert-type scale, with 1 denoting 'strongly disagree' and 5 denoting 'strongly agree'. In order to check the reliability and validity of the scale, the pilot test was conducted in which a total of 53 participants took part, the result of which was favourable, prompting the researchers to put the questionnaire for the final survey. Contents of the measuring items are presented in Table 1.

Table 1. Study Items, Sources and SEM Loadings.

Study constructs and items	Source(s)	SEM loadings
Conceptual knowledge		
FL1. When an investor spreads his money among different assets, the risk of losing money decreases.	Van Rooij et al. (2011)	0.68
FL2. Considering a long period (for example, 10 or 20 years), stock normally gives the highest return.	Van Rooij et al. (2011)	0.78
FL3. Normally, stock displays the highest fluctuation over time.	Van Rooij et al. (2011)	0.73
Accounting Information		
FL4. I have the capability to analyse the company's financial statements and annual reports.	Calcagno and Monticone (2015); Heshmat (2012)	0.68
FL5. I have sufficient knowledge about various financial analysis tools (financial ratios, cash flow statements, and fund flow statements)	Calcagno and Monticone (2015)	0.61
FL6. I have good knowledge of the price-earnings ratio and its impact on future stock prices.	Calcagno and Monticone (2015)	0.74
FL7.I have the ability to assess various economic indicators (GDP, inflation, interest rate etc.) and their impact on stock prices.	Calcagno and Monticone (2015)	0.86
Technical knowledge		
FL08: I have the ability to apply various statistical tools (viz., average, correlation, regression, S.D.).	Jappelli & Padula (2013); Islamoğlu et al. (2015)	0.80

(Table 1 continued)

(Table 1 continued)

Study constructs and items	Source(s)	SEM loadings
Conceptual knowledge		
FL09: Technical analysis helps investors to predict future movement in stock prices.	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.69
FL10: I have sufficient knowledge about various tools of technical analysis (charts, indicators, etc)_	Jappelli & Padula (2013); Islamoğlu et al. (2015)	0.70
Market Information		
FL11. I have sufficient information about the particular industry in the market for the purpose of investment.	Calcagno and Monticone (2015); Jappelli and Padula (2015)	0.75
FL12. I have sufficient information regarding various investment alternatives in the financial market.	Mouna and Anis (2017)	0.68
FL13. If the interest rate falls, the price of the bond rises.	Worthington (2013); Van Rooij et al. (2011)	0.72
Investment decision		
ID1. I invest in the stock market frequently.	Raut (2020)	0.63
ID2. I encourage my close friends to invest in the stock market.	Raut (2020)	0.66
ID3. I will invest in the stock market soon.	Raut (2020)	0.62
ID4. I invest only after doing a Fundamental analysis of the stock.	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.71
ID5. I invest after doing a technical analysis of the stock.	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.77
ID6. I invest after considering the current economic indicators.	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.80
ID7. I invest after looking into the fluctuations/development in the major stock indices (Nifty/Sensex)	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.78
ID 8. I invest after looking into the company's market capitalisation.	Hassan Al-Tamimi & Anood Bin Kalli (2009)	0.73

Sample Design and Data Collection

This research is undertaken to examine the influence of subjective FL on the factors affecting the investment decisions of individual investors. To achieve this objective, we have selected individual retail investors who participate in the Indian stock market as the target population for this study. Choosing the appropriate sample size is essential for any study to be high-quality and rigorous (Farooq et al., 2018). For this motive, Schreiber et al. (2006) proposed the 10 times rule, which was also suggested by Hair Jr et al. (2023) to figure out the minimum sample size required for data analysis in Partial Least Squares Structural Equation Modeling (PLS-SEM). As per this guideline, the minimum sample should be '10 times the largest number of structural paths directed at a particular construct in the structural model'. Accordingly, the minimum number of respondents for the sample should be 40, given that the structural model for this study consists of five constructs (four independent variables and one dependent variable).

However, based on the review of previous related studies, the sample size of our study was finalised. A purposive sampling procedure was used to distribute the questionnaire among 300 individual investors in India to collect the requisite data, and a total of 230 filled-in questionnaires were obtained, revealing a response rate of 76.67%. An identical response rate was obtained in the latest study by Adil et al. (2022), who got a 74% response rate while measuring the FL of individual investors.

Analytical Methods

The present study used IBM SPSS 23.0 and Smart PLS 3 software to analyse the data. Reflective measurement models are included in the conceptual framework of our research. We have employed PLS-SEM, which can also operate on a reflective measurement model apart from handling measured construct. Furthermore, PLS-SEM was selected based on its ability 'to evaluate causal relationships among all latent constructs simultaneously while dealing with measurement errors in the structural model' (Farooq & Radovic-Markovic, 2016; Hair Jr et al., 2023). Following Hair Jr et al. (2023) recommendation, the researchers began by assessing the measurement model before evaluating the structural model. However, before going for PLS-SEM analysis, we evaluated the data using prescribed statistical tests, including the common-method bias (CMB) test and data screening for missing values. These procedures and additional validity and reliability checks helped us determine the quality of the data.

Data Analysis and Results

Common-method Bias Test

A one-factor Harman test is carried out to determine if CMB exists among the variables. Moreover, suggestions by Podsakoff et al. (2003) were complied with while carrying out this test. For this reason, every element of the measurement scale was loaded into SPSS to perform principal axis factoring using varimax rotation. The result shows that while considering a single factor, it can describe inconsistency that accounts for 28.693%, which is lower than the 50% criteria and does not raise any concern for CMB in the current study. The outcome of the one-factor Harman test is shown in Table 2.

Table 2. Harman One-factor Test.

Component	Total	Extraction Sums of Square Loadings % of Variance	Cumulative %
1	6.025	28.693	28.693

Data Screening and Pre-analysis

Extensive data scrutiny was conducted before the data analysis process. Researchers test the normality, outliers, missing values and demographic profiles of the data collected for any possibility of statistical error. However, no missing values were found in the data.

A quick overview of the demographic characteristics of respondents in terms of their gender, age group, educational qualification, employment status and monthly income is presented before starting data analysis and discussing the study's findings. There were 230 respondents; out of the total, males and females were 64.35% and 35.65%, respectively. Nearly 81.7% of those who participated in the survey are aged 18–25. For educational qualification, 53.9% of the respondents had undergraduate degrees, 26.1% were postgraduates and 12.8% had passed intermediate. About 17.3% of the respondents were full-time salaried, 8.3% were part-time and 23.8% were students. Also, about 72.2% earn less than ₹10,000, and 11.1% earn between ₹10,000 and ₹20,000. Appendix A gives descriptive statistics of the respondents (see the Appendix section).

Analysis of Measurement Model

As mentioned earlier, the conceptual model of this research involves only reflective measurement models. All five constructs, that is, conceptual knowledge, accounting information, technical knowledge, market information and investment decisions are reflectively measured constructs. These reflective measurement models were independently analysed following Hair Jr et al. (2023) and Henseler et al. (2009) recommendations. All constructs' reliability and validity were assessed to evaluate the reflective measurement models. The result showed that factor loadings, which is the simple correlation between indicators and constructs, are above the acceptable threshold of 0.50.

Moreover, composite reliability and Cronbach's alpha values for all constructs were computed, and these measures were found to be above the 0.70 critical level recommended by Cohen (1988). The AVE value for each construct exceeded the specified limit of 0.50, as recommended by Hair Jr et al. (2023). Table 3 lists all constructs' reliability and validity values.

Furthermore, the Fornell–Larcker criterion was applied to examine the discriminant validity of all constructs, as illustrated in Table 4. The correlation coefficients are lower than the square root of AVE, which is shown in bold in Table 4, thus confirming the discriminant validity of the reflectively measured

Table 3. Validity and Reliability of Latent Constructs.

Latent Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Conceptual knowledge	0.78	0.78	0.54
Accounting information	0.82	0.83	0.53
Technical knowledge	0.77	0.77	0.53
Market information	0.76	0.76	0.52
Investment decision	0.89	0.89	0.51

Table 4. Discriminant Validity (Fornell–Larcker Criterion).

Latent Constructs	Conceptual Knowledge	Conceptual Knowledge	Conceptual Knowledge	Conceptual Knowledge	Conceptual Knowledge
Conceptual knowledge	**0.73**				
Accounting information	0.22	**0.73**			
Technical knowledge	0.38	0.55	**0.73**		
Market information	0.22	0.51	0.43	**0.72**	
Investment decision	0.32	0.52	0.50	0.70	**0.72**

Note: Bold values signify that the correlation coefficients are lower than the square root of AVE.

constructs (Hair Jr et al., 2023). As a result, all conditions for establishing the reliability and validity of the reflective measurement model are satisfied.

To further examine the discriminant validity, we computed the HTMT ratio of correlations, following the recommendation of Henseler et al. (2015). According to the guidelines, 'HTMT value greater than 0.85 indicates a potential problem of discriminant validity' (Hair Jr et al., 2023). In this study, HTMT values were lying well below the critical value of 0.85, indicating no problem of discriminant validity (see Table 5).

Analysis of the Structural Model

For the purpose of evaluating the structural model in this study, overall explanatory power (represented by R^2 value), predictive relevance (shown by Q^2 value) and path coefficient beta values are examined. The outcome of the structural model is shown in Figure 2.

Table 5. Discriminant Validity (HTMT Ratio).

Latent Constructs	Conceptual Knowledge	Accounting Information	Technical Knowledge	Market Information	Investment Decision
Conceptual knowledge					
Accounting information	0.22				
Technical knowledge	0.38	0.55			
Market information	0.22	0.51	0.43		
Investment decision	0.32	0.51	0.50	0.70	

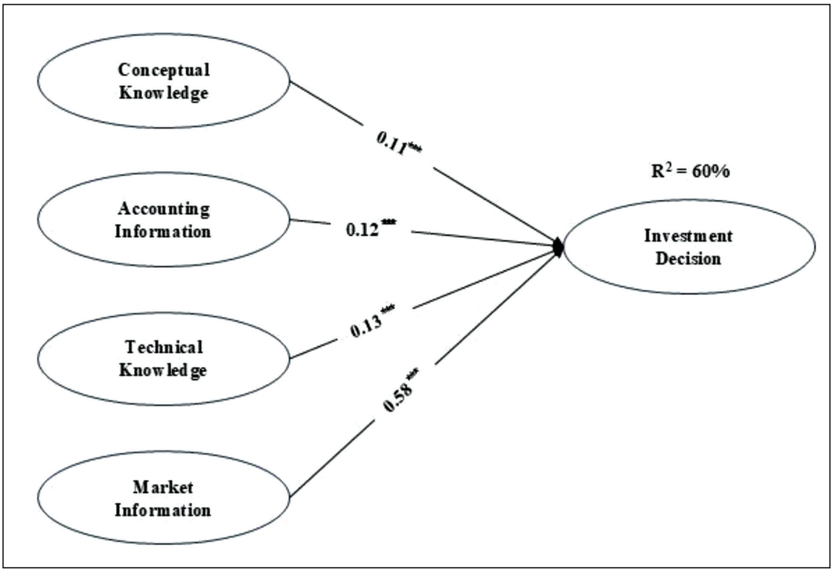


Figure 2. Results of the Structural Model.

The result shows that $R^2 = 0.60$, demonstrating that the proposed model can explain 60% of the variance in the investment decision. Moreover, the relationship between conceptual knowledge and investment decision ($\beta = 0.11$; $p < .001$) is found to be positive and statistically significant, confirming H_1. Likewise, H_2 is also accepted, indicating a positively significant association between accounting information and investment decisions ($\beta = 0.12$; $p < .001$). Similarly, H_3 is also supported, demonstrating a significant association between technical knowledge and investment decisions ($\beta = 0.13$; $p < .001$). Lastly, a significant and positive association between market information and investment decisions is also found,

Table 6. Hypothesis Assessment.

Hypothesised Path	β Value	p Value	Decision
H_1. Conceptual knowledge → investment decision	0.11	<.001	Supported
H_2. Accounting information → investment decision	0.12	<.001	Supported
H_3. Technical knowledge → investment decision	0.13	<.001	Supported
H_4. Market information → investment decision	0.58	<.001	Supported

Note: β represents standardised regression weights.

thus supporting H_4 (β = 0.58; p < .001). Table 6 presents the findings of the hypothesis assessment (see Figure 2).

According to Figure 2, our proposed model has an R^2 value of 60%, indicating sufficient explanatory power. Here, caution is warranted, as it is not a good viewpoint to endorse the model simply relying on the R^2 value (Farooq & Radovic-Markovic, 2016; Hair Jr et al., 2023). Therefore, the predictive relevance of the structural model should also be examined using Wold and Bertholet's (1982) Q^2 value. Accordingly, latent exogenous constructs in the structural model are generally agreed upon to have predictive relevance for latent endogenous constructs if the Q^2 value exceeds zero (Chin, 1998; Hair Jr et al., 2023). In this study, Q^2 value = 0.254 indicates strong predictive relevance in the endogenous construct (investment decisions), thus supporting the underlying assumptions of this study. This analysis also found no issue of collinearity. This achieves the overall predictive relevance of our model.

Discussion and Conclusion

The current work tries to explain the influence of subjective FL on the investment decisions of individual investors in India. Therefore, after a thorough review of the literature, the conceptual framework of the current work was grounded on the four crucial aspects of FL, that is, Conceptual knowledge, accounting information, technical knowledge and market information were taken as independent factors influencing the dependent factor, that is, investment decisions. The acceptance of all the study hypotheses (H_1–H_4) in SEM analysis indicated that FL is crucial when making an informed investment decision; these findings align with the contributions of the prior related works (Fedorova et al., 2015; Hilgert et al., 2003; Jariwala, 2015; Prasad et al., 2021). These outcomes indicated that the degree of FL of investors influences their ability to make investment decisions to a large extent, as Jariwala (2015) has shown. Financially literate investors tend to make wiser investment decisions (Hilgert et al., 2003). Also, the SEM analysis showed that the four main factors of FL: conceptual knowledge, accounting information, technical knowledge and market information explained 60% variance (R^2 of 60%) in the investment decisions of the investors, indicating the explanatory power of the conceptual model of the study.

Considering the findings of the SEM analysis, all proposed hypotheses are accepted, supporting the outcomes of the prior related studies; the present work has shown that all the mentioned dimensions of FL influence investors' investment decisions in India (Hassan Al-Tamimi & Anood Bin Kalli, 2009; Jariwala, 2015; Prasad et al., 2021). Acceptance of H_1 confirms that conceptually sound investors' investment decisions are not irrational because their investments are grounded on their conceptual knowledge of the associated risk and return. Also, the acceptance of H_2 confirms that enhanced accounting information leads to better investment decision-making by individual investors. This indicates that individual investors' investment decisions are rational and sound because they prefer to analyse the company's balance sheets before investing in its stock. These findings are consistent with the previous studies in this area. For example, Nagy and Obenberger (1994) and Prasad et al. (2021) also reported that individual investor behaviour is impacted by the quality of accounting information they possess.

Acceptance of H_3 and H_4 confirmed that technical knowledge and market information significantly affect the investment decisions of individual investors, indicating that technically sound investors with proper details of the financial markets tend to perform technical analysis of the stocks using mean, variance and SD before investing in the selected stocks. Additionally, they tend to compare different alternatives available for investment, and for this purpose, they analyse the overall market in general and particular industry in specific. Moreover, they analyse all the available information on the market, including interest rates and prices of bonds. These results endorse the findings of Prasad et al. (2021), who also reported that technical knowledge and market information were significantly associated with investment decisions. Additionally, our research found that the top three influencing factors affecting investment decisions were the past performance of the firm's stock, the result of fundamental analysis and the condition of the financial statement. Also, focusing on the demographics of the study participants, it is evident that most young investors are willing to invest in the stock market after analysing the market and performing fundamental and technical analyses. They prefer to look into the stocks and market capitalisation of the company, and they tend to examine the economic policies and conditions of the economy before finalising their investment.

Furthermore, the R^2 value obtained in the SEM analysis indicated the robustness and explanatory capabilities of the present study's conceptual model. Therefore, we argue that the current study's conceptual framework has fulfilled its objective of explaining individual investors' investment decisions by focusing on FL. Hence, the proposed framework can be applied in studies on individual investors' decisions in other economies, specifically developing economies similar to India, such as Bhutan, Sri Lanka and Bangladesh.

Implications

This research has multiple practical implications for the government, policymakers, financial advisors and individual investors. This study showed that the dimensions of FL have a significant and positive association with investment decisions. Therefore, it is suggested that the concerned stakeholders, like managers and policymakers in government, should focus on appropriate measures to improve individual investors' FL, considering its various dimensions like conceptual knowledge, accounting information, technical knowledge and market information that could help them in better investment decision-making. Furthermore, the necessity of enhancing FL has grown as a result of the creation of innovative financial products, the intricacy of the financial markets and the complexity of using financial technology to help investors manage their finances and safeguard them from substantial financial loss in future (Hassan Al-Tamimi & Anood Bin Kalli, 2009). The government should incorporate voluntary FL programmes in the curriculum for school/college students to equip them with the required knowledge and skills to make profitable investment decisions and achieve their financial well-being. They may also use social media to reach the masses and enhance their FL.

It is worth mentioning that although savings in India are the highest in the world, the engagement of Indian investors in the stock market is shallow (Sivaramakrishnan et al., 2017). The major reason why investors do not participate in the stock market is because they do not comprehend movement in the market and information, rise and fall in stock, stock market trends, legal procedures and other prerequisites for participation in the stock market (Adil et al., 2022). Hence, this study explains that FL can help individual investors make better investment decisions and increase their participation in the stock market (de Bassa Scheresberg, 2013).

Limitations and Future Research Directions

This research evaluates individual investors' perception of their FL and how it affects their investment decisions. This research may be extended by examining how FL impacts saving and credit decisions. The sample of the present work was gathered from individual Indian investors only; therefore, future research may be conceptualised on a cross-cultural, cross-national or cross-state basis better to understand the investor's behaviour from different segments of populations, as the same was found in earlier related works (Manocha et al., 2023). The same research may also be conducted in India's other states and regions, as well as in nations where the issue of FL has not been thoroughly examined by academicians or policymakers or where only preliminary research has been conducted. The conceptual model of the present work can also be used in future research by including important investor-related factors like awareness, perceptions and so on. (Kaur & Kaushik, 2016). Retail individual investors with investments under ₹200,000 were the target population for this study. Future studies can approach high-net-worth individuals to determine whether FL affects investment decisions.

Appendix

Appendix A. Investors Demographics Attributes.

Attributes	Distribution	Frequency	Percentage
Gender	Male	148	64.35
	Female	82	35.65
Age group	18–25	188	81.7
	26–35	40	17.2
	36–45	2	1.1
	46–55	Nil	Nil
Educational qualification	High school	2	1.1
	Intermediate	30	12.8
	Graduation	124	53.9
	Post-graduation	60	26.1
	Doctorate	14	6.1
Employment status	Full-time salaried	40	17.3
	Part-time salaried	19	8.3
	Self-employed	6	2.8
	Retired	Nil	Nil
	Student	55	23.8
	Unemployed	110	47.8
Monthly income	Less than 10,000	166	72.2
	10,001–20,000	27	11.1
	20,001–30,000	11	5
	30,001–40,000	11	5
	40,001–50,000	6	2.8
	More than 50,000	9	3.9

Acknowledgements

The authors are grateful to the journal referees for their constructive suggestions to improve the quality of the article.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Fahad https://orcid.org/0000-0001-8755-5284

References

Adil, M., Singh, Y., & Ansari, M. S. (2022). Does financial literacy affect investor's planned behavior as a moderator? *Managerial Finance*, *48*(9/10), 1372–1390.

Allgood, S., & Walstad, W. B. (2016). The effects of perceived and actual financial literacy on financial behaviors. *Economic Inquiry*, *54*(1), 675–697.

Amari, M., & Anis, J. (2021). Exploring the impact of socio-demographic characteristics on financial inclusion: Empirical evidence from Tunisia. *International Journal of Social Economics*, *48*(9), 1331–1346.

Ansari, Y., Albarrak, M. S., Sherfudeen, N., & Aman, A. (2023). Examining the relationship between financial literacy and demographic factors and the overconfidence of Saudi investors. *Finance Research Letters*, *52*, 103582.

Baker, H. K., & Haslem, J. A. (1974). Toward the development of client-specified valuation models. *The Journal of Finance*, *29*(4), 1255–1263.

Bellofatto, A., D'Hondt, C., & De Winne, R. (2018). Subjective financial literacy and retail investors' behavior. *Journal of Banking and Finance*, *92*, 168–181.

Bernheim, D. (1998). Financial illiteracy, education and retirement saving. *Living with defined contribution pensions*. University of Pennsylvania.

Bucher-Koenen, T., & Ziegelmeyer, M. (2011). *Who lost the most? Financial literacy, cognitive abilities, and the financial crisis* [Working Paper Series, No. 1299, European Central Bank].

Calcagno, R., & Monticone, C. (2015). Financial literacy and the demand for financial advice. *Journal of Banking & Finance*, *50*, 363–380.

Chandra, A., & Kumar, R. (2011). *Determinants of individual investor behaviour: An orthogonal linear transformation approach*. https://ssrn.com/abstract=1790713

Chawla, D., Bhatia, S., & Singh, S. (2022). Parental influence, financial literacy and investment behaviour of young adults. *Journal of Indian Business Research*, *14*(4), 520–539.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295–336.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cole, S., Sampson, T., & Zia, B. (2011). Prices or knowledge? What drives demand for financial services in emerging markets? *The Journal of Finance*, *66*(6), 1933–1967.

de Bassa Scheresberg, C. (2013). Financial literacy and financial behavior among young adults: Evidence and implications. *Numeracy*, *6*(2), 5.

Farooq, M. S., & Radovic-Markovic, M. (2016). Modeling entrepreneurial education and entrepreneurial skills as antecedents of intention towards entrepreneurial behaviour in single mothers: A PLS-SEM approach. *Entrepreneurship: Types, Current Trends and Future Perspectives*, *198*, 216.

Farooq, M. S., Salam, M., Fayolle, A., Jaafar, N., & Ayupp, K. (2018). Impact of service quality on customer satisfaction in Malaysia airlines: A PLS-SEM approach. *Journal of Air Transport Management*, *67*(September 2017), 169–180.

Fedorova, E. A. E., Nekhaenko, V. V., & Dovzhenko, S. E. E. (2015). Impact of financial literacy of the population of the Russian Federation on behavior on financial market: Empirical evaluation. *Studies on Russian Economic Development*, *26*, 394–402.

French, D., & McKillop, D. (2016). Financial literacy and over-indebtedness in low-income households. *International Review of Financial Analysis*, *48*, 1–11.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, *32*, 1–36.

Graham, J. R., Harvey, C. R., & Huang, H. (2009). Investor competence, trading frequency, and home bias. *Management Science*, *55*(7), 1094–1106.

Hair Jr, J. F., Hair, J., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2023). *Advanced issues in partial least squares structural equation modeling*. Sage Publications.

Hassan Al-Tamimi, H. A., & Anood Bin Kalli, A. (2009). Financial literacy and investment decisions of UAE investors. *The Journal of Risk Finance*, *10*(5), 500–516.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*, 115–135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *New challenges to international marketing*. Emerald Group Publishing Limited.

Heshmat, N. A. (2012). Analysis of the capital asset pricing model in the Saudi stock market. *International Journal of Management*, *29*(2), 504.

Hilgert, M. A., Hogarth, J. M., & Beverly, S. G. (2003). Household financial management: The connection between knowledge and behavior. *Federal Reserve Bulletin*, *89*, 309.

Islamoğlu, M., Apan, M., & Ayvalı, A. (2015). Determination of factors affecting individual investor behaviours: A study on bankers. *International Journal of Economics and Financial Issues*, *5*(2), 531–543.

Jappelli, T., & Padula, M. (2015). Investment in financial literacy, social security, and portfolio choice. *Journal of Pension Economics & Finance*, *14*(4), 369–411.

Jariwala, H. V. (2015). Analysis of financial literacy level of retail individual investors of Gujarat state and its effect on investment decision. *Journal of Business and Finance Librarianship*, *20*, 133–158.

Karlsson, N., Dellgran, P., Klingander, B., & Gärling, T. (2004). Household consumption: Influences of aspiration level, social comparison, and money management. *Journal of Economic Psychology*, *25*(6), 753–769.

Kaur, I., & Kaushik, K. P. (2016). Determinants of investment behaviour of investors towards mutual funds. *Journal of Indian Business Research*, *8*(1), 19–42.

Lusardi, A., & Mitchell, O. S. (2007a). Baby boomer retirement security: The roles of planning, financial literacy, and housing wealth. *Journal of Monetary Economics*, *54*(1), 205–224.

Lusardi, A., & Mitchelli, O. S. (2007b). Financial literacy and retirement preparedness: Evidence and implications for financial education: The problems are serious, and remedies are not simple. *Business Economics*, *42*, 35–44.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *American Economic Journal: Journal of Economic Literature*, *52*(1), 5–44.

Lusardi, A., Michaud, P. C., & Mitchell, O. S. (2017). Optimal financial knowledge and wealth inequality. *Journal of Political Economy*, *125*(2), 431–477.

Maditinos, D. I., Šević, Ž., & Theriou, N. G. (2007). Investors' behaviour in the Athens Stock Exchange (ASE). *Studies in Economics and Finance*, *24*(1), 32–50.

Manocha, S., Bhullar, P. S., & Sachdeva, T. (2023). Factors determining the investment behaviour of farmers—The moderating role of socioeconomic demographics. *Journal of Indian Business Research*, *15*(3), 301–317.

Mathew, V., PK, S. K., & Sanjeev, M. A. (2024). Financial well-being and its psychological determinants—An emerging country perspective. *FIIB Business Review*, *13*(1), 42–55.

Merikas, A. A., Merikas, A. G., Vozikis, G. S., & Prasad, D. (2004). Economic factors and individual investor behavior: The case of the Greek stock exchange. *Journal of Applied Business Research (JABR)*, *20*(4). https://doi.org/10.19030/jabr.v20i4.2227

Merkle, C., & Weber, M. (2014). Do investors put their money where their mouth is? Stock market expectations and investing behavior. *Journal of Banking and Finance*, *46*, 372–386.

Moore, D. L. (2003). *Survey of financial literacy in Washington State: Knowledge, behavior, attitudes, and experiences*. Washington State Department of Financial Institutions.

Mouna, A., & Anis, J. (2017). Financial literacy in Tunisia: Its determinants and its implications on investment behavior. *Research in International Business and Finance*, *39*, 568–577.

Nagy, R. A., & Obenberger, R. W. (1994). Factors influencing individual investor behavior. *Financial Analysts Journal*, *50*(4), 63–68.

Noctor, M., Stoney, S., & Stradling, R. (1992). *Financial literacy: Discussion of concepts and competences of financial literacy and opportunities for its introduction into young people's learning*. National Foundation for Educational Research.

OECD. (2005). *Improving financial literacy: Analysis of issues and policies*. OECD. https://doi.org/10.1787/9789264012578-en

Ouachani, S., Belhassine, O., & Kammoun, A. (2021). Measuring financial literacy: A literature review. *Managerial Finance*, *47*(2), 266–281.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879.

Prasad, S., Kiran, R., & Sharma, R. K. (2021). Influence of financial literacy on retail investors' decisions in relation to return, risk and market analysis. *International Journal of Finance and Economics*, *26*(2), 2548–2559.

Rai, K., Dua, S., & Yadav, M. (2019). Association of financial attitude, financial behaviour and financial knowledge towards financial literacy: A structural equation modeling approach. *FIIB Business Review*, *8*(1), 51–60.

Raut, R. K. (2020). Past behaviour, financial literacy and investment decision-making process of individual investors. *International Journal of Emerging Markets*, *15*(6), 1243–1263.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, *99*(6), 323–338.

Sivaramakrishnan, S., Srivastava, M., & Rastogi, A. (2017). Attitudinal factors, financial literacy, and stock market participation. *International Journal of Bank Marketing*, *35*(5), 818–841.

Suresh, G. (2024). Impact of financial literacy and behavioural biases on investment decision-making. *FIIB Business Review*, *13*(1), 72–86.

Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, *101*(2), 449–472.

Wold, H., & Bertholet, J. L. (1982). The PLS (partial least squares) approach to multidimensional contingency tables. *Metron*, *40*(1–2), 303–326.

Worthington, A. C. (2013). Financial literacy and financial literacy programmes in Australia. *Journal of Financial Services Marketing*, *18*, 227–240.

Article

Traces of Herd Behaviour Over a Decade in Indian Stock Markets

MDIM Journal of Management Review and Practice
3(1) 37–54, 2025

DOI: 10.1177/mjmrp.241290586
mbr.mjmrp.mdim.ac.in

Nagendra Marisetty[1] and Kompalli Sasi Kumar[2]

Abstract

This study investigates herd behaviour in the Indian Stock Market from 2011 to 2020, analysing daily returns of stocks listed in the S&P BSE 500 index. By employing the Chang, Cheng and Khorana model, the research assesses the presence and impact of herding behaviour across various market conditions, industry sectors and timeframes. The findings reveal nuanced patterns of investor behaviour, with evidence of herd behaviour particularly pronounced during down-market conditions, as indicated by negative and statistically significant coefficients of cross-sectional absolute dispersion returns. Sector-specific analysis unveils varying degrees of herd behaviour, with strong evidence observed in the capital goods and IT sectors, while banking displays a propensity for independent decision-making. The study identifies market capitalization and year-wise variations in herd behaviour, highlighting the dynamic nature of investor sentiment and its implications for market functioning and stability. This comprehensive empirical analysis contributes to a deeper understanding of herd behaviour in the Indian Stock Market, offering valuable insights for investors, policymakers and market participants. The study underscores the importance of considering contextual factors, such as market conditions and industry dynamics, in analysing investor behaviour and its impact on market dynamics. The findings have practical implications for informed decision-making and regulatory interventions aimed at promoting market efficiency and resilience. By elucidating the drivers and consequences of herd behaviour across different dimensions, this research enhances our knowledge of investor behaviour and lays the groundwork for

[1]REVA Business School, REVA University, Bangalore, Karnataka, India
[2]GITAM School of Business (GSB-H)—Hyderabad, GITAM Deemed to Be University, Hyderabad, Telangana, India

Corresponding author:
Kompalli Sasi Kumar, GITAM School of Business (GSB-H)—Hyderabad, GITAM Deemed to Be University, Hyderabad, Telangana 502329, India.
E-mails: skompall@gitam.edi; sasikumarkompalli@gmail.com

further studies in this area, emphasizing the need for ongoing research to navigate the complexities of financial markets and ensure their stability and integrity.

Keywords

CSAD returns, Chang model, herd behaviour, Indian Stock Market, S&P BSE 500 Index

Introduction

The study investigates herd behaviour in the Indian Stock Market through an empirical analysis of daily returns for a comprehensive sample of stocks over a period spanning from 2011 to 2020. By examining the presence and impact of herd behaviour across different market conditions, industry sectors, and timeframes, the study aims to provide insights into the dynamics of investor behaviour and its implications for market functioning and stability. Herd behaviour, wherein investors imitate the actions of others rather than independently evaluating market information, has been widely studied in financial markets worldwide. However, its prevalence, drivers and consequences vary across different contexts, making it a subject of ongoing research and debate. In the Indian Stock Market, previous studies have provided insights into herd behaviour, but a comprehensive analysis spanning multiple dimensions is lacking.

To address this gap, the present study conducts a detailed examination of herd behaviour using a diverse set of methodologies and datasets. The analysis begins with a review of existing literature on herd behaviour in financial markets, synthesizing findings from studies conducted in various regions, sectors and timeframes. By drawing on this rich body of research, the study establishes a framework for understanding the nuanced nature of herd behaviour and its implications for market dynamics. The empirical analysis focuses on daily returns for a sample of stocks listed on the Indian Stock Market, encompassing different market capitalizations, industry sectors and time periods. Regression analysis is employed to assess the impact of market conditions, such as up and down-market phases, on the manifestation of herd behaviour. Additionally, the study examines industry-specific patterns of herd behaviour to identify sectoral differences in investor behaviour.

The findings of the study provide valuable insights into the dynamics of herd behaviour in the Indian Stock Market. By elucidating the presence, drivers and consequences of herd behaviour across different dimensions, the study contributes to a deeper understanding of investor behaviour and its implications for market functioning and stability. Moreover, the study offers practical implications for investors, policymakers and market participants, informing decision-making processes and regulatory interventions aimed at promoting market efficiency and resilience. Overall, the study advances our knowledge of herd behaviour in the Indian Stock Market and underscores the importance of considering contextual factors and methodological approaches in studying investor behaviour. Through its rigorous empirical analysis and comprehensive review of literature, the study enhances our understanding of the complexities inherent in financial markets and lays the groundwork for further research in this area.

Literature Review

Herding behaviour in financial markets has been a subject of significant interest and investigation, with numerous studies exploring its presence, dynamics and implications across different markets and periods. This review synthesizes findings from a diverse range of studies spanning various regions, methodologies and timeframes, shedding light on the nuanced nature of herding behaviour and its impact on market dynamics.

Several studies focus on specific regional markets, such as European markets (Brendea et al., 2019; Mobarek et al., 2014) or emerging markets like South Africa (Sarpong, 2014), India (Ansari & Ansari, 2021; Kumar & Bharti, 2017; Prosad et al., 2012), Malaysia (Brahmana et al., 2012), Pakistan (Ahmad & Wu, 2022), Sri Lanka (Abeysekera et al., 2020), Jordan (Ramadan, 2015) and Taiwan (Demirer et al., 2010), providing insights into the prevalence and drivers of herding behaviour in these contexts. These studies highlight the influence of market conditions, regulatory frameworks, and investor behaviour on herd formation, with implications for market stability and investor returns. European stock markets, Caporale et al. (2008) studied Athens Stock Market and found evidence for herd behaviour in extreme market conditions. Khan et al. (2011) investigate herding behaviour in French, German, Italian and English markets, finding its prevalence during normal market fluctuations but noting its absence during periods of market turmoil. However, the study's limited focus on four markets highlights the need for broader research encompassing diverse market conditions and geographical regions.

Others explore herding behaviour across multiple markets, securities or sectors, revealing cross-market tendencies (BenMabrouk, 2018; Chiang & Zheng, 2010), or sector-specific variations (Musah et al., 2022), Private Equity Industry (Buchner et al., 2020), commodity markets (Steen & Gjolberg, 2013) or options markets (Bernales et al., 2015). Such studies underscore the interconnectedness of global financial markets and the differential impact of herding across industries and securities, offering valuable insights for investors and policymakers. Further exploration into market-specific herding dynamics reveals nuanced patterns. Litimi (2017) focuses on the French stock market during crisis periods, uncovering sector-specific herding behaviour and its impact on market volatility. Similarly, Hudson et al. (2018) delve into UK fund managers' herding behaviour, emphasizing the role of investor sentiment in shaping institutional herding and its implications for market stability and regulation.

Methodological innovations also feature prominently in the literature, with studies introducing novel measures (Hwang et al., 2001), testing methodologies (Ganesh et al., 2018), Monday irrationality (Brahmana et al., 2012), pension funds (Koetsier & Bikker, 2023), sub-prime crisis in the emerging European markets (Filip et al., 2015) or exploring intraday herding (Henker et al., 2006), enhancing our understanding of herd behaviour and its drivers. Additionally, experimental studies (Azofra et al., 2006) provide controlled environments to examine herding tendencies, offering complementary insights into investor decision-making. Theoretical frameworks, such as those proposed by Hirshleifer and Teoh (2001), offer insights into the underlying mechanisms driving herding behaviour. By delineating incentives for herding and cascading and emphasizing rational social learning models, these frameworks provide a broader perspective on capital market behaviours. Moreover, Saumitra and Sidharth (2014) used cross-sectional distribution approach rather than the traditional standard deviation approach for testing herd behaviour in the Indian Stock Market.

Despite the breadth of research, inconsistencies and debates persist. Some studies find evidence of herding during market downturns (Chang et al., 2000; Christie & Huang, 1995), while others observe herding during calm periods (Hwang et al., 2001), reflecting the complex interplay of factors shaping investor behaviour. Moreover, studies on market efficiency and information transmission (Da & Shive, 2017; Tan & Chiang, 2005) highlight the role of herding in price formation and market efficiency, with implications for asset pricing models and investment strategies. Studies from emerging markets provide valuable insights into herding behaviour across different economic contexts. Tauseef (2023) explores herding behaviour in the Pakistan Stock Exchange, highlighting its prevalence during crises and calendar events, while Bui et al. (2015) examine Southeast Asian markets, emphasizing the role of institutional investors in driving herding behaviour and the need for regulatory measures.

Moreover, empirical evidence challenges conventional perceptions and sheds light on unique market dynamics. Rubbaniy et al. (2012) challenge the notion of passive trading among Dutch pension funds, revealing significant herding behaviour and feedback trading strategies. Similarly, studies on Latin American (Vieito et al., 2022) and Vietnamese (Tessaromatis & Thomas, 2009) markets uncover strong herding tendencies and market-specific influences on herding behaviour. Kumar and Bharti (2017) investigate herding behaviour in the Indian equity market, specifically in the IT sector. Their findings challenge prior assumptions, indicating a lack of conclusive evidence of herding in Indian IT sector stocks. Similarly, Kanojia et al. (2020) explore herd behaviour in the Indian Stock Market, revealing no discernible evidence of herding over a decade-long period, attributed to the dominance of institutional investors. Even, Javaira & Hassan (2015) found no evidence for herd behaviour in Pakistan markets except during the liquidity crisis.

Moving to Latin American markets, Lavin and Magner (2013) delve into Chilean equity mutual funds, uncovering intentional herding effects attributed to agency problems and investor biases. Additionally, Vieito et al. (2022) investigate herding behaviour in the Latin American Integrated Market (MILA), highlighting its prevalence under specific market conditions and its sensitivity to time-varying volatilities. Exploring Asian markets, Yao et al. (2013) examine herding behaviour in Chinese A and B stock markets, revealing varying levels of herding across market segments and industries. Furthermore, Medhioub and Chaffai (2017) focus on Islamic stock markets in the Gulf Cooperation Council (GCC), identifying significant herding behaviour in Saudi and Qatari markets during downturns, Ah Mand et al. (2023) observed herd behaviour between Islamic and conventional markets.

Studies also delve into the theoretical underpinnings of herding behaviour and its implications for market dynamics. Shapira et al. (2014) propose a novel model treating stock markets as networks of investors, capturing key characteristics of market behaviour and correlations. Additionally, Wang and Sun (2014) provide competitive models explaining investors' use of technical analysis, shedding light on rational information discovery versus irrational herding behaviour. Further, exploring unique market conditions and events, Shantha (2019) investigates herding behaviour in the Colombo Stock Exchange of Sri Lanka, revealing evolving patterns influenced by political instability and speculative bubbles. Similarly, Gavriilidis et al. (2007) examine herding behaviour during the Argentine financial crisis, offering insights into its evolution amidst market turmoil.

Lastly, studies on investor behaviour and decision-making dynamics contribute to our understanding of herding phenomena. Sachdeva et al. (2021) identify key motivators for herding behaviour among Indian stock investors, offering practical implications for informed decision-making and policymaking. Moreover, Stavroyiannis and Babalos (2018) uncover negative herding behaviour in Eurozone markets, with implications for portfolio diversification strategies.

Herd behaviour was observed during market crisis of 1999 and surprisingly investors became cautious after 2002. Studies investigated the linkage between volatility and herding (Blasco et al., 2012) in Spanish markets with intraday samples. Results indicated a direct linear effect of herding on volatility (realized and implied). Herding measurement variables need to be considered, while predicting volatility. Studies conducted on Indian bourses (Madaan & Shrivastava, 2022; Sahoo et al., 2023) revealed a positive and significant association between herding and volume turnover, volatility, information asymmetry. Further studies examined herding in two different shades as value-based herding and count-based herding. Both separate herding ratio, as buy side and sell side based on the positive and negative values of the ratio as well as to investigate their impact on asset prices. Often studies observed herding in investment houses (both domestic and foreign) recommendations (Ahluwalia et al., 2017) relating to specific stocks. Explored the behaviour by applying event study methodologies and found that CAAR is negative, insignificant for large cap, mid-cap stocks.

Herding by the institutional investors like mutual funds, venture capital firms, hedge fund houses in bond market is higher than equities. In US bond markets (Cai et al., 2019), sell-side herding is more prevalent than buy-side herding. Impact of this herding on prices is also highly asymmetric in nature. Generally, in equity markets institutional herding is low and evidences are presented in small stocks and growth funds.

Traces of herding by pension funds and mutual funds in stocks are lower, but in small-cap stocks it is higher (Lakonishok et al., 1992; Wermers, 1999) and in low-rating bonds like junk bonds category, herding is substantially higher. Few studies examined industry herding, FIIs herding in association with stock market returns, trading volume (displayed an inverse relationship with herding) and volatility periods (Choudhary et al., 2022; Madaan & Panda, 2023; Sahoo et.al., 2023) revealed a positive relationship between FIIs, lagged market returns and herding. Presence of close nexus is evident between stock market returns and herding in India. Cumulative returns response to buy-side and sell-side herding is contrasting. Sell-side herding of FIIs producing return reversals and cumulative returns are decreasing in a short period. Stock prices are falling below their intrinsic values in case of sell-side herding.

Chinese stock markets displayed that COVID-19 pandemic (Fei & Zhang, 2023) related herd behaviour has negative effect on stock market stability. Significant presence of herd behaviour is observed during COVID-19. There is also an asymmetry exits in herd behaviour between bull and bear markets. Herd behaviour affects the market volatility negatively (Choudhary et al., 2022).

After major economic turbulences like financial crisis, pandemic and subprime crisis, current research works on herding, isolating the behaviour of institutional investors at individual level and investigating the influence of individual institutional investors on the market. Till date, research experienced a combined effect of domestic and foreign institutional investors. FIIs exhibits (Sahoo et al., 2023) a tendency to reproduce the investment behaviour of their peers and this characteristic leads to herding in the financial markets. FIIs herding adversely affecting the stock prices and in energy stocks buy-side herding dominating sell-side herding (Madaan & Panda, 2023; Madaan & Shrivastava, 2022). Numerous studies found out a strong association between COVID-19 pandemic and uncertainty raised in the financial markets due to flow of herd information (Bouri et al., 2021) among investors. Specifically, emerging markets' and European markets; response to the herding during COVID-19 is more impactful.

In conclusion, the literature on herding behaviour offers a rich tapestry of insights into the dynamics of financial markets, emphasizing the multifaceted nature of investor behaviour and its implications for market functioning and stability. While the evidence points to the presence of herding across various contexts, further research is warranted to elucidate its drivers, consequences and potential mitigation strategies, particularly in the context of evolving market structures and regulatory frameworks.

Methodology

The dataset utilized in this study encompasses firms listed in the S&P BSE 500 Index, which collectively represent more than 90% of India's total market capitalization. Established on 9 August 1999, the index comprises 500 firms spanning across various sectors of the Indian economy. Daily data spanning from 1 January 2011 to 31 December 2020, inclusive of the volatile year of 2020, were analysed to explore investor herding behaviour, particularly during the COVID-19 period. This data period is critical for analysis due to few noteworthy events happened during this period like market recovery after the Satyam scandal (2009), NSEL scam (2013), aftermath of demonetization in the markets (2016), and COVID-19 pandemic (2020) events brought down the markets to extremely low levels. It is closely observed that every five-year cycle, these systemic risk events creating a market disturbance, which needs to be examined thoroughly with market wide herding measures. Retail investors participation increased to 45% in the year 2021 and retail accounts with NSDL (19.7 lakh new accounts added as on 2021) and CDSL (122.5 lakh new accounts added as on 2021) representing an exponential growth in terms of numbers. Buffet indicator (ratio of market capitalization to GDP) also increasing steadily in the economy during the study period, as a result, the period of the study became a key factor for analysis. The data were sourced from the S&P BSE website, ensuring the inclusion of all active firms throughout the study period to reduce survivorship bias. The study scrutinized herd behaviour within the S&P BSE 500 Index over a decade from 2011 to 2020, examining various cross-sectional dimensions, including market capitalization, industry-wise analysis, and year-wise categories such as large cap (69 stocks), mid-cap (73 stocks), small cap (200 stocks), as well as the full sample (372 stocks), across up and down markets.

To investigate herding behaviour, the study employed the Chang, Cheng and Khorana (CCK) model, chosen over the Christie and Huang model due to its capacity to capture herding across a broader spectrum of returns, encompassing normal returns, and its recognition of the linear relationship between equity return dispersion and market conditions (Chang et al., 2000). The CCK model was considered more suitable for analysing daily return data, offering insights into short-lived herding behaviour, which is particularly pertinent given the volatility and sensitivity of markets. This methodology facilitates a comprehensive understanding of investor behaviour under diverse market conditions and timeframes, thereby contributing valuable insights into the dynamics of the Indian Stock Market.

The study conducted by Chang et al. (2000) introduces rational asset pricing models suggesting a linear, increasing relationship between cross-sectional absolute dispersion (CSAD) and the absolute market return. However, in instances where investors exhibit herding behaviour, characterized by mimicking others' actions and individual returns aligning with the overall market return, a negative, significant nonlinear relationship between CSAD and overall market return emerges, marked by a negative coefficient of ($R_{m,t}$). CSAD, representing the average dispersion of securities, is computed as the absolute average of the difference between the expected individual security return and market return.

$$\mathrm{CSAD}_t = \frac{1}{N}\sum_{(i=0)}^{n} \left| R_{i,t} - R_{m,t} \right| \tag{1}$$

$$\mathrm{CSAD}_t = \alpha + \beta_1 \left| R_{m,t} \right| + \beta_2 \left(R_{m,t} \right)^2 + \varepsilon_t \tag{2}$$

In Equation (1), CSAD represents the average dispersion of the securities, where $R_{m,t}$ denotes the absolute market return on day $R_{i,t}$ represents the stock return of security at time t, and N is the number of firms in the portfolio. Moving to Equation (2), $R_{m,t}$ signifies the absolute market return, while $(R_{m,t})^2$ represents the squared market return. A positive and statistically significant coefficient of β_1 in Equation (2) indicates that asset pricing model predictions remain unviolated. Conversely, a significantly negative β_2 suggests the presence of herding behaviour. To assess the asymmetric effects of herding in both up and down markets, the study employs the subsequent equations.

$$\mathrm{CSAD}_t^{\mathrm{UP}} = \alpha + \beta_1^{\mathrm{UP}} \left| R_{m,t}^{\mathrm{UP}} \right| + \beta_2^{\mathrm{UP}} \left(R_{m,t}^{\mathrm{UP}} \right)^2 + \varepsilon_t \tag{3}$$

$$\mathrm{CSAD}_t^{\mathrm{DOWN}} = \alpha + \beta_1^{\mathrm{DOWN}} \left| R_{m,t}^{\mathrm{DOWN}} \right| + \beta_2^{\mathrm{DOWN}} \left(R_{m,t}^{\mathrm{DOWN}} \right)^2 + \varepsilon_t \tag{4}$$

In this context, $R_{m,t}^{\mathrm{UP}}$ and $R_{m,t}^{\mathrm{DOWN}}$ represent the absolute value of the equally weighted portfolio return of stocks on day t for up and down markets, respectively. Here, $R_{m',t} > 0$ indicates an up market, while $R_{m',t} < 0$ indicates a down market. Negative and statistically significant coefficients of β_2^{UP} and β_2^{DOWN} indicate evidence of herding in up and down markets, respectively, while positive and significant coefficients of β_2^{UP} and β_2^{DOWN} demonstrate negative herding.

Analysis and Interpretation

Table 1 presents descriptive statistics for the returns of CSAD and the S&P BSE 500 Index, providing insights into their performance characteristics. First, the mean return for CSAD stands notably higher at 0.343194 compared to the S&P BSE 500 Index's mean return of 0.033398, indicating that CSAD has historically yielded superior average returns. Moreover, CSAD exhibits lower volatility with a standard deviation of 0.304867, contrasting sharply with the S&P BSE 500 Index's higher standard deviation of 1.073053, implying that CSAD's returns are less dispersed around its mean.

Additionally, the skewness of CSAD's returns is positive (1.982013), suggesting a right-skewed distribution with a tail extending towards higher returns, while

Table 1. Descriptive Statistics of CSAD and S&P BSE 500 Index Returns.

Details	CSAD	S&P BSE 500 Returns
Mean	0.343194	0.033398
Standard error	0.006126	0.02156
Median	0.268243	0.106971
Standard deviation	0.304867	1.073053
Sample variance	0.092944	1.151443
Kurtosis	6.589138	16.67515
Skewness	1.982013	−1.33354
Range	2.571757	21.28246
Minimum	2.68E-05	−13.7891
Maximum	2.571784	7.493311
Sum	850.0923	82.728
Count	2,477	2,477
Confidence level (95.0%)	0.012012	0.042278

the S&P BSE 500 Index's returns exhibit negative skewness (−1.33354), indicating a left-skewed distribution with a tail towards lower returns. Both CSAD and the S&P BSE 500 Index display high kurtosis, implying heavier tails in their return distributions compared to a normal distribution. Furthermore, the range of CSAD returns (2.571757) is narrower than that of the S&P BSE 500 Index (21.28246), reflecting less variability in CSAD returns. These statistics collectively underscore the differences in distributional properties, volatility and central tendency between CSAD and the broader market represented by the S&P BSE 500 Index.

Table 2 contains regression results for CSAD returns, categorized by different market conditions (full sample, up market and down market) and different time frames (daily, weekly and monthly returns). In the case of daily returns for the full sample, β_2 is not statistically significant. This suggests that there is no evidence of herd behaviour affecting daily returns in the full sample. In the up-market condition for daily returns, β_2 is positive but not statistically significant. This may indicate a lack of herd behaviour during up-market conditions on a daily basis. In the down-market condition for daily returns, β_2 is negative and statistically significant at the 5% level. This implies that there is evidence of herd behaviour impacting CSAD returns during down-market conditions on a daily basis. Investors may be more likely to follow the crowd when markets are performing poorly.

Table 2. CSAD Returns of the Full Sample, Up Market and Down Market.

Returns	Details	β_0	β_1	β_2	*F* Statistics
Daily returns (372 stocks)	Full sample	0.2457***	0.1413***	−0.0021	147.6717***
		(.0000)	(.0000)	(.2561)	(.0000)
	Up market	0.2704***	0.0380*	0.0369***	114.0576***
		(.0000)	(.0744)	(.0000)	(.0000)
	Down market	0.2514***	0.1421***	−0.0052**	65.2343***
		(.0000)	(.0000)	(.0132)	(.0000)
Weekly returns (372 stocks)	Full sample	0.0062***	0.2009***	−0.9547*	20.4686***
		(.0000)	(.0000)	(.0811)	(.0000)
	Up market	0.0067***	0.1629**	−0.3302	9.8851***
		(.0000)	(.0156)	(.7271)	(.0001)
	Down market	0.0056***	0.2261***	−1.2754*	11.0722***
		(.0000)	(.0003)	(.0633)	(.0000)
Monthly returns (372 stocks)	Full sample	0.0187***	−0.0574	0.8885**	7.2116***
		(.0000)	(.4121)	(.0113)	(.0011)
	Up market	0.0172***	0.0293	−0.2205	0.0173
		(.0000)	(.8543)	(.8686)	(.9829)
	Down market	0.0179***	0.0125	0.6871	6.4887***
		(.0000)	(.9107)	(.1423)	(.0031)

Note: *p* values in parenthesis. Statistically significant *@ 10% level, **@ 5% level and ***@ 1% level.

For weekly and monthly returns, β_2 is also negative in some cases but not statistically significant, except for weekly returns in the full sample and down-market, where it is significant at the 10% level. This suggests that herd behaviour might have a more noticeable impact on CSAD returns during down-market conditions over weekly time frame. It is important to consider the practical implications of these findings. The negative and significant β_2 values during down-market conditions on a daily and weekly basis suggest that investors might be more prone to herd behaviour during market downturns. This behaviour could lead to greater market volatility and potentially exacerbate market declines as investors react to each other's actions.

Table 3 depicts the full sample for large-cap stocks β_2 is −0.0010, and it is not statistically significant (p = .6145), there is no statistically significant evidence of herd behaviour affecting CSAD returns. In up-market conditions for large-cap stocks, β_2 is positive (0.0117) and significant at the 5% level (p = .0356). This indicates that there is no evidence of herd behaviour. In down-market conditions for large-cap stocks, β_2 is negative (−0.0029) but not statistically significant, suggesting limited evidence of herd behaviour impacting CSAD returns during market downturns. In the full sample for mid-cap stocks β_2 is −0.0045, and it is

Table 3. CSAD Daily Returns of the Stocks Segregated Based on the Market Capitalization Wise.

Capitalization	Details	β_0	β_1	β_2	*F* Statistics
Large cap (69 stocks)	Full sample	0.2180***	0.0862***	−0.0010	49.5623***
		(.0000)	(.0000)	(.6145)	(.0000)
	Up market	0.2263***	0.0457**	0.0117**	25.4154***
		(.0000)	(.0471)	(.0356)	(.0000)
	Down market	0.2235***	0.0946***	−0.0029	27.0798***
		(.0000)	(.0000)	(.1957)	(.0000)
Mid-cap (73 stocks)	Full sample	0.1806***	0.0656***	−0.0045***	30.7878***
		(.0000)	(.0000)	(.0032)	(.0000)
	Up market	0.1924***	0.0386*	0.0024	10.2060***
		(.0000)	(.0608)	(.7081)	(.0000)
	Down market	0.1761***	0.0756***	−0.0055***	20.7731***
		(.0000)	(.0000)	(.0012)	(.0000)
Small cap (230 stocks)	Full sample	0.1327***	0.0403***	0.0002	58.4114***
		(.0000)	(.0000)	(.8657)	(.0000)
	Up market	0.1482***	0.0078	0.0127***	24.5853***
		(.0000)	(.5923)	(.0079)	(.0000)
	Down market	0.1266***	0.0438***	−0.0004	37.6720
		(.0000)	(.0000)	(.7121)	(.0000)

Note: *p* values in parenthesis. Statistically significant *@ 10% level, **@ 5% level and ***@ 1% level.

statistically significant at the 1% level (p = .0032), there is strong evidence of herd behaviour negatively impacting CSAD returns. In up-market conditions for mid-cap stocks β_2 is 0.0024, and it is not statistically significant (p = .7081), there is no statistically significant evidence of herd behaviour affecting CSAD returns. In down-market conditions for mid-cap stocks β_2 is −0.0055, and it is statistically significant at the 1% level (p = .0012), there is strong evidence of herd behaviour negatively impacting CSAD returns.

In the full sample for small-cap stocks β_2 is 0.0002, and it is not statistically significant (p = .8657), there is no statistically significant evidence of herd behaviour affecting CSAD returns. In up-market conditions for small-cap stocks β_2 is 0.0127, and it is statistically significant at the 5% level (p = .0079). This indicates that there is no evidence of herd behaviour. In down-market conditions for small-cap stocks, β_2 is negative (−0.0004) and it is not statistically significant (p = .7121), suggesting limited evidence of herd behaviour impacting CSAD returns during market downturns. In mid-cap stocks, there is strong evidence of herd behaviour, particularly in full sample and down markets, negatively impacting returns. Large-cap stocks show some evidence of herd behaviour in full sample and down markets, but the effect is less pronounced. Small-cap stocks exhibit less evidence of herd behaviour in down markets, negatively affecting returns, but the effect is not statistically significant. These findings suggest that the impact of herd behaviour varies by market capitalization and market conditions, with mid-cap stocks being most affected by herd behaviour, particularly during market downturns. Investors in small-cap stocks tend to follow the crowd in down markets, leading to negative returns, but the effect is less significant during up markets.

Table 4 provides the analysis of CSAD daily returns across different industry sectors in reveals distinct patterns of investor behaviour, shedding light on the presence of herd behaviour in the Indian Stock Market. Notably, the banking industry stands out as a sector where investors seem to act independently, as indicated by a positively significant β_2 coefficient. This suggests that during the daily trading of banking stocks, investors do not tend to follow the crowd, making decisions that are more individualistic. In contrast, the capital goods industry presents a striking example of herd behaviour, with a negatively significant β_2. In this sector, investors exhibit a propensity to imitate the actions of others, potentially leading to suboptimal investment decisions. This divergence in behaviour across industries underscores the impact of sector-specific factors, market dynamics and investor sentiment in shaping trading decisions.

While herd behaviour is evident in the capital goods sector, other industries such as IT and Utilities also show positively significant β_2 coefficients. These findings imply that herd behaviour, where investors collectively influence returns, is not confined to a single direction. Rather, it can manifest as both positive and negative influences on CSAD returns within different industry contexts. Furthermore, the absence of statistically significant β_2 coefficients in the FMCG and healthcare sectors indicates that, in these industries, investor decisions appear to be driven by factors other than herding behaviour. This underscores the multifaceted nature of financial markets, where the interplay of industry-specific

Table 4. CSAD Daily Returns of Stocks Segregated Based on Industry Wise.

Industry	β_0	β_1	β_2	*F* Statistics
Auto (14 stocks)	0.3264***	0.0998***	−0.0047	21.4454*
	(.0000)	(.0000)	(.1133)	(.0000)
Banking (20 stocks)	0.5104***	0.0692***	0.0103***	59.3666***
	(.0000)	(.0010)	(.0001)	(.0000)
Capital goods (19 stocks)	0.2820***	0.3762***	−0.0105***	360.2211***
	(.0000)	(.0000)	(.0003)	(.0000)
Energy (17 stocks)	0.5230***	0.2098***	0.0090**	161.2376***
	(.0000)	(.0000)	(.0179)	(.0000)
Finance (38 stocks)	0.3979***	0.1073***	0.0047**	92.6215***
	(.0000)	(.0000)	(.0249)	(.0000)
FMCG (27 stocks)	0.4150***	0.3216***	−0.0071	168.8281***
	(.0000)	(.0000)	(.1831)	(.0000)
Healthcare (41 stocks)	0.4021***	0.1247***	0.0029	57.3926***
	(.0000)	(.0000)	(.5556)	(.0000)
IT (26 stocks)	0.6507***	0.1438***	0.0372***	287.5293***
	(.0000)	(.0000)	(.0000)	(.0000)
Metal (12 stocks)	0.4288***	0.0021	0.0078**	8.3749***
	(.0000)	(.9297)	(.0457)	(.0002)
Utilities (13 stocks)	0.3572***	0.0358	0.0148***	38.0567***
	(.0000)	(.1038)	(.0018)	(.0000)

Note: *p* values in parenthesis. Statistically significant *@ 10% level, **@ 5% level and ***@ 1% level.

variables and investor sentiment leads to varying degrees of herding or independent decision-making.

The analysis of industry-wise CSAD daily returns underscores the dynamic nature of investor behaviour in the Indian Stock Market. The presence and direction of herd behaviour vary across sectors, with the banking industry characterized by independent decision-making, the capital goods sector exhibiting strong herd behaviour, and others displaying a mix of both positive and negative influences. These results emphasize the crucial role of sector-specific dynamics, market conditions, and individual investor sentiment in shaping investment choices, providing valuable insights for market participants and policymakers.

Table 5 provides data on CSAD weekly returns for stocks segregated based on year wise (from 2011 to 2020) in the Indian Stock Market. The table includes coefficients β_0, β_1, and β_2, along with *F* statistics, with *p* values indicating statistical significance. In 2020, there is clear and statistically significant evidence of herd behaviour. The β_2 coefficient is negatively significant, indicating that investors exhibited herd behaviour. This suggests that during 2020, investors

Table 5. CSAD Values of Full Sample Segregated Based on Year Wise.

Details	β_0	β_1	β_2	*F* Statistics
Year 2011 (372 stocks)	0.3095***	−0.0042	0.0390	9.8387***
	(.0000)	(.9508)	(.1135)	(.0000)
Year 2012 (372 stocks)	0.2256***	0.0278	0.0282	8.5123***
	(.0000)	(.6815)	(.3402)	(.0003)
Year 2013 (372 stocks)	0.2639***	0.0594	0.0412*	27.8814***
	(.0000)	(.3224)	(.0556)	(.0000)
Year 2014 (372 stocks)	0.3661***	−0.1821	0.1978***	18.0786***
	(.0000)	(.1181)	(.0006)	(.0000)
Year 2015 (372 stocks)	0.3099***	−0.0343	0.0388***	21.8701***
	(.0000)	(.3984)	(.0000)	(.0000)
Year 2016 (372 stocks)	0.2528***	0.0207	0.0524*	17.3555***
	(.0000)	(.7663)	(.0538)	(.0000)
Year 2017 (372 stocks)	0.2653***	−0.2012**	0.2162***	10.4249***
	(.0000)	(.0251)	(.0005)	(.0000)
Year 2018 (372 stocks)	0.2625***	0.2022**	−0.0347	6.4095***
	(.0000)	(.0464)	(.4541)	(.0019)
Year 2019 (372 stocks)	0.2833***	0.0467	0.0055	2.5302*
	(.0000)	(.3964)	(.7246)	(.0817)
Year 2020 (372 stocks)	0.2802***	0.1967***	−0.0091**	26.6828***
	(.0000)	(.0000)	(.0169)	(.0000)

Note: *p* values in parenthesis. Statistically significant *@ 10% level, **@ 5% level and ***@ 1% level.

collectively influenced stock returns by moving along with the prevailing sentiment. This herd behaviour may have been driven by factors unique to that year, such as the COVID-19 pandemic and economic uncertainty.

In the years 2013, 2014, 2015, 2016 and 2017, there is no statistically significant evidence of herd behaviour. During these years, β_2 is positively significant, suggesting that investors were not significantly influenced by the actions of others, and market dynamics were driven by factors other than traditional herd behaviour. These years represent periods where investors may have made decisions independently or reacted to market conditions based on factors other than following the crowd. In the remaining years, 2011, 2012, 2018 and 2019, there is also no statistically significant evidence of herd behaviour. β_2 is not significantly negative, indicating that herd behaviour, as defined by negatively significant β_2, was not observed. These findings highlight the complex and dynamic nature of investor behaviour over the years, where herd behaviour can manifest differently in different periods, driven by a variety of market dynamics and sentiment factors.

Scope and Limitations of the Study

The study tested herd behaviour in S&P BSE 500 Index across various segments ranging from industry to stock classification along with different phases in the market. Future studies can be further extended to explore the presence of herd behaviour in sectoral, thematic and innovative indices so that regulators may caution the market participants, namely retail investors, institutional investors and government about the abnormalities. Herd behaviour can be further tested across various markets like Emerging VS Developed, BRICS VS MENA, G7 VS G20, Asian Economies and so on to explore the risk spill overs to sensitize about asset bubbles, market crashes. Research delineated towards market wide herding, than institutional investors herding. More research needs to happen in the area of institutional investors herding like mutual funds, pension funds, insurance companies and so on. This is one of the shortcomings of this research. As herding measures are innate in nature, there may be a chance that results are affected by the outliers.

This study helps the policy makers in fixing the market-wide circuit breakers during extreme market moments. Retail investors' participation in stock markets soaring to new heights in the recent past, there is also possibility of dominating non-fundamental herding patterns. As herding is a relative concept and a phenomenon of social contagion, it needs to be monitored and controlled.

Conclusion

Based on an empirical investigation spanning from 2011 to 2020, this study delves into herd behaviour in the Indian Stock Market, focusing on the daily returns of stocks listed in the S&P BSE 500 Index. Employing the CCK model, the research scrutinizes herd behaviour across diverse market conditions, industry sectors and timeframes. Results unveil nuanced patterns, with herd behaviour notably pronounced during down-market conditions, especially evident through negative and statistically significant coefficients of CSAD returns. A sector-specific analysis further reveals varying degrees of herd behaviour, with strong evidence observed in capital goods and IT sectors, while banking displays a propensity for independent decision-making. Moreover, the study identifies market capitalization and year-wise variations in herd behaviour, emphasizing the dynamic nature of investor sentiment and its implications for market functioning and stability.

This comprehensive empirical analysis contributes significantly to understanding herd behaviour in the Indian Stock Market, offering valuable insights for investors, policymakers and market participants. The study underscores the importance of considering contextual factors such as market conditions and industry dynamics when analysing investor behaviour and its impact on market dynamics. Practical implications highlight the need for informed decision-making and regulatory interventions aimed at enhancing market efficiency and resilience. By elucidating drivers and consequences of herd behaviour across different dimensions, this research enhances knowledge of investor behaviour and lays the groundwork for further studies in this area, emphasizing the ongoing need for research to navigate financial market complexities and ensure stability and integrity.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iDs

Kompalli Sasi Kumar https://orcid.org/0000-0003-3816-1793

Nagendra Marisetty https://orcid.org/0000-0003-3939-5794

References

Abeysekera, S. M., Wijesinghe, D. C., & Weligamage, S. S. (2020). An examination of herd behaviour: Evidence from Colombo Stock Exchange. *SSRN Electronic Journal*, 197–209. https://doi.org/10.2139/ssrn.3889078

Ah Mand, A., Janor, H., Abdul Rahim, R., & Sarmidi, T. (2023). Herding behaviour and stock market conditions. *PSU Research Review*, *7*(2), 105–116. https://doi.org/10.1108/PRR-10-2020-0033

Ahluwalia, N. S., Gupta, M., & Aggarwal, N. (2017). Stock buy recommendations and their impact: Evidence from Indian capital markets. *Abhigyan*, *XXXV*(2), 28–41.

Ahmad, M., & Wu, Q. (2022). Does herding behaviour matter in investment management and perceived market efficiency? Evidence from an emerging market. *Management Decision*, *60*(8), 2148–2173. https://doi.org/10.1108/MD-07-2020-0867

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

Azofra, V., Fernández., B., & Vallelado., E. (2006). An experimental study of herding and contrarian behavior among financial investors. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.932928

BenMabrouk, H. (2018). Cross-herding behaviour between the stock market and the crude oil market during financial distress: Evidence from the New York Stock Exchange. *Managerial Finance*, *44*(4), 439–458. https://doi.org/10.1108/MF-09-2017-0363

Bernales, A., Verousis, T., & Voukelatos, N. (2015). *Do investors follow the herd in option markets?* https://doi.org/10.2139/ssrn.3336268

Blasco, N., Corredor, P., & Ferreruela, S. (2012). Does herding affect volatility? Implications for the Spanish stock market. *Quantitative Finance*, *12*(2), 311–327. https://doi.org/10.1080/14697688.2010.516766

Bouri, E., Demirer, R., Gupta, R., & Nel, J. (2021). COVID-19 pandemic and investor herding in international stock markets. *Risks*, *9*, 168. https://doi.org/10.3390/risks9090168

Brahmana, R., Hooy, C. W., & Ahmad, Z. (2012). The role of herd behaviour in determining the investor's Monday irrationality. *Asian Academy of Management Journal of Accounting and Finance*, *8*(2), 1–20.

Brendea, G., & Pop, F. (2019). Herding behaviour and financing decisions in Romania. *Managerial Finance*, *45*(6), 716–725. https://doi.org/10.1108/MF-02-2018-0093

Buchner, A., Mohamed, A., & Schwienbacher, A. (2020). Herd behaviour in buyout investments. *Journal of Corporate Finance*, *60*(*August*). https://doi.org/10.1016/j.jcorpfin.2019.101503

Bui, N. D., Nguyen, L. T. B., & Nguyen, N. T. T. (2015). Herd behaviour in Southeast Asian Stock Markets—An empirical investigation. *Acta Oeconomica*, *65*(3), 413–429. https://doi.org/10.1556/032.65.2015.3.4

Cai, F., Han, S., Li, D., & Li, Y. (2019). Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics*, *131*, 139–167.

Caporale, G. M., Economou, F., Philippas, N., & London, W. (2008). Herd behaviour in extreme market conditions. *Economics Bulletin*, *7*(17), 1–13. https://bura.brunel.ac.uk/handle/2438/3462%0A

Chang, E.C., Cheng, J.W., & Khorana, A. (2000). An examination of herd behaviour in equity markets: An international perspective. *Journal of Banking and Finance*, *24*(10), 1651–1679.

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

Choudhary, K., Singh, P., & Soni, A. (2022). Relationship between FIIs' herding and returns in the Indian equity market: Further empirical evidence. *Global Business Review*, *23*(1), 137–155. https://doi.org/10.1177/0972150919845223

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal*, *51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

Da, Z., & Shive, S. (2017). Exchange traded funds and asset return correlations. *European Financial Management*, *24*(1), 136–168. https://doi.org/10.1111/eufm.12137

Demirer, R., Kutan, A. M., & Chen, C. D. (2010). Do investors herd in emerging stock markets? Evidence from the Taiwanese market. *Journal of Economic Behaviour and Organization*, *76*(2), 283–295. https://doi.org/10.1016/j.jebo.2010.06.013

Fei, F., & Zhang, J. (2023). Chinese stock market volatility and herding behaviour asymmetry during the COVID-19 pandemic. *Cogent Economics & Finance*, *11*, 2203436. https://doi.org/10.1080/23322039.2023.2203436

Filip, A., Pochea, M., & Pece, A. (2015). The herding behaviour of investors in the CEE stocks markets. *Procedia Economics and Finance*, *32*(15), 307–315. https://doi.org/10.1016/s2212-5671(15)01397-0

Ganesh, R., Gopal, N., & Thiyagarajan, S. (2018). Bulk and block holders herding behaviour. *South Asian Journal of Business Studies*, *7*(2), 150–171. https://doi.org/10.1108/SAJBS-12-2017-0139

Gavriilidis, C., Kallinterakis, V., & Micciullo, P. (2007). The Argentine crisis: A case for herd behaviour? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.980685

Henker, J., Henker, T., & Mitsios, A. (2006). Do investors herd intraday in Australian equities? *International Journal of Managerial Finance*, *2*(3), 196–219. https://doi.org/10.1108/17439130610676475

Hirshleifer, D. A., & Teoh, S. H. (2001). Herd behaviour and cascading in capital markets: A review and synthesis. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4380872

Hudson, Y. B., Yan, M., Zhang, D., & Hudson, Y. (2018). *Herd behaviour & investor sentiment: Evidence from UK mutual funds provisional draft: Not for quotation*. https://ssrn.com/abstract=3222312

Hwang, S., & Salmon, M. (2001). *A new measure of herding and empirical evidence*, C.U. School (Éd.) [CUBS Financial Econometrics Working Paper No. WP01-12].

Javaira, Z., & Hassan, A. (2015). An examination of herding behaviour in Pakistani stock market. *International Journal of Emerging Markets*, *10*(3), 474–490. https://doi.org/10.1108/IJoEM-07-2011-0064

Jirasakuldech, B., & Emekter, R. (2021). Empirical analysis of investors' herding behaviours during the market structural changes and crisis events: Evidence from Thailand, *Global Economic Review*, *50*(2), 139–168. https://doi.org/10.1080/1226508X.2020.1821746

Kanojia, S., Singh, D., & Goswami, A. (2020). Impact of herding on the returns in the Indian Stock Market: An empirical study. *Review of Behavioural Finance*, *14*(1), 115–129. https://doi.org/10.1108/RBF-01-2020-0017

Khan, H., Hassairi, S. A., & Viviani, J.-L. (2011). Herd behaviour and market stress: The case of four European countries. *International Business Research*, *4*(3), 53–67. https://doi.org/10.5539/ibr.v4n3p53

Koetsier, I., & Bikker, J. A. (2023). Herd behaviour of pension funds by asset class. *International Journal of Economics and Finance*, *15*(2), 26. https://doi.org/10.5539/ijef.v15n2p26

Kumar, A. Bharti. (2017). Herding in Indian Stock Markets: An evidence from information technology sector. *IOSR Journal of Economics and Finance*, 1–7. https://www.iosrjournals.org/iosr-jef/papers/(SIFICO)-2017/Volume-1/1.%2001-07.pdf

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *31*

Lavin, J. F., & Magner, N. S. (2013). Herding in the mutual fund industry: Evidence from Chile. *Academia Revista Latinoamericana de Administracion*, *27*(1), 10–29. https://doi.org/10.1108/ARLA-09-2013-0137

Litimi, H. (2017). Herd behaviour in the French stock market. *Review of Accounting and Finance*, *16*(4), 497–515. https://doi.org/10.1108/RAF-11-2016-0188

Madaan, V., & Panda, L. (2023). Determinants of industry herding in the Indian Stock Market. *Business Perspectives and Research*. https://doi.org/10.1177/22785337231176870

Madaan, V., & Shrivastava, M. (2022). FIIs herding in energy sector of Indian Stock Market. *South Asian Journal of Business Studies*, *11*(2), 174–194. https://doi.org/10.1108/SAJBS-02-2020-0033

Medhioub, I., & Chaffai, M. (2017). Islamic finance and herding behaviour: An application to Gulf Islamic stock markets. *Review of Behavioural Finance*, *10*(2), 192–206. https://doi.org/10.1108/RBF-02-2017-0014

Mobarek, A., Mollah, S., & Keasey, K. (2014). A cross-country analysis of herd behaviour in Europe. *Journal of International Financial Markets, Institutions and Money*, *32*(1), 107–127. https://doi.org/10.1016/j.intfin.2014.05.008

Musah, G., Domeher, D., & Alagidede, I. (2022). Effect of presidential elections on investor herding behaviour in African stock markets. *International Journal of Emerging Markets*, *19*(5), 1157–1177. https://doi.org/10.1108/IJOEM-06-2021-0960

Prosad, J. M. P., Kapoor, S., & Sengupta, J. (2012). An examination of herd behaviour: An empirical evidence from Indian Equity Market. *International Journal of Trade, Economics and Finance*, *3*(2), 2–5.

Ramadan, I. Z. (2015). Cross-sectional absolute deviation approach for testing the herd behaviour theory: The case of the ASE Index. *International Journal of Economics and Finance*, *7*(3), 188–193. https://doi.org/10.5539/ijef.v7n3p188

Rubbaniy, G., van Lelyveld, I., & Verschoor, W. (2012). *Herding behaviour and trading among Dutch pension funds*. Mimeo, Erasmus School of Economics.

Sachdeva, M., Lehal, R., Gupta, S., & Garg, A. (2021). What make investors herd while investing in the Indian Stock Market? A hybrid approach. *Review of Behavioural Finance*, *15*(1), 19–37. https://doi.org/10.1108/RBF-04-2021-0070

Sahoo, G. S., Rajvanshi V., Syamala, S. R. (2023). *Herd behaviour of institutional investors: Evidence from an emerging market*. Working Paper-IIM Kozhikode.

Sarpong, P. K. (2014). Against the herd: Contrarian investment strategies on the Johannesburg Stock Exchange. *Journal of Economics and Behavioural Studies*, *6*(2), 120–129. https://doi.org/10.22610/jebs.v6i2.475

Saumitra, B., & Sidharth, M. (2012). Applying an alternative test of herding behaviour: A case study of the Indian Stock Market. *MPRA Munich Personal RePEc Archive*. https://mpra.ub.uni-muenchen.de/38014/

Shantha, K. V. A. (2019). The evolution of herd behaviour: Will herding disappear over time? *Studies in Economics and Finance*, *36*(3), 637–661. https://doi.org/10.1108/SEF-06-2018-0175

Shapira, Y., Berman, Y., & Ben-Jacob, E. (2014). Modelling the short-term herding behaviour of stock markets. *New Journal of Physics*, *16*. https://doi.org/10.1088/1367-2630/16/5/053040

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

Steen, M., & Gjolberg, O. (2013). Are commodity markets characterized by herd behaviour? *Applied Financial Economics*, *23*(1), 79–90. https://doi.org/10.1080/09603107.2012.707770

Tan, L., & Chiang, T. (2005). *Empirical analysis of Chinese stock market behavior: Evidence from dynamic correlations, herding behavior, and speed of adjustment* [PhD thesis, Drexel University].

Tauseef, S. (2023). Herd behaviour in an emerging market: An evidence of calendar and size effects. *Journal of Asia Business Studies*, *17*(3), 639–655. https://doi.org/10.1108/JABS-10-2021-0430

Tessaromatis, N., & Thomas, V. (2009). Herding behaviour in the Athens Stock Exchange. *Investment Management and Financial Innovations*, *6*(3), 156–164.

Vieito, J. P., Espinosa, C., Wong, W. K., Batmunkh, M. U., Choijil, E., & Hussien, M. (2022). Herding behaviour in integrated financial markets: The case of MILA. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-08-2021-1202

Wang, T., & Sun, Q. (2014). Why investors use technical analysis? Information discovery versus herding behaviour. *China Finance Review International*, *5*(1), 53–68. https://doi.org/10.1108/CFRI-08-2014-0033

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance*, *54*(2), 581–622. http://www.jstor.org/stable/2697720

Yao, J., Ma, C., & He, W. P. (2013). Investor herding behaviour of Chinese stock market. *International Review of Economics and Finance*, *29*, 12–29. https://doi.org/10.1016/j.iref.2013.03.002

Article

Impact of Emojis on Customer Purchasing Behaviour in Social Media Marketing of E-commerce Industries with Reference to Flipkart and Amazon

MDIM Journal of Management Review and Practice
3(1) 55–67, 2025

DOI: 10.1177/mjmrp.241304553
mbr.mjmrp.mdim.ac.in

Surjadeep Dutta[1], R. Arivazhagan[1], Rebecca Balasundaram[2], Shyamaladevi. B[1] and Raj Singh[1]

Abstract

This study examines the impact of emojis on consumer buying behaviour in social media marketing. With the rise of visual digital communication, emojis have become potent instruments for expressing emotions and augmenting interaction. This study investigates the impact of emojis on customer emotions, perceptions, and purchasing decisions in social media commercials, postings, and promotional content. The research seeks to comprehend the impact of emoji-driven marketing campaigns on customer responses across several platforms, specifically on brand communication, customer engagement, and sales performance. The collection of quantitative data involves the analysis of various characteristics, including Brand Communication, Sales Performance, and Customer Engagement. Qualitative data are acquired through interviews with people employed in Social Media marketing businesses such as Flipkart and Amazon. Additionally, questionnaires are administered to candidates who have had experiences with the information system. Total of approximately 200 samples have been gathered for this investigation. Data collection has taken place in Bangalore. The gathered data have been imported into the IBM SPSS database for subsequent analysis, including chi-square analysis and regression

[1]Faculty of Management, SRM Institute of Science & Technology, Kattankulathur, Tamil Nadu, India
[2]School of Computer Science, York St John University, London Campus, London, UK

Corresponding author:
Surjadeep Dutta, Faculty of Management, SRM Institute of Science & Technology, Kattankulathur, Tamil Nadu 603203, India.
E-mail: surjadeepdutta@gmail.com

analysis. The results indicate that Emojis play a big part in brand communication; thus, e-commerce managers require a systematic approach to social media marketing. The high influence of customer involvement on emoji usage in e-commerce social media marketing offers managers a strategic opportunity to connect with their audience. E-commerce firms can boost client engagement by using emoticons, fostering interactive content, analysing consumer preferences, and being active on social media.

Keywords

Brand communication, customer engagement, emoji, sales performance, social media marketing

Introduction

The incorporation of emojis in social media marketing has profoundly influenced consumer purchase behaviour by augmenting emotional involvement and communication. Emojis, as visual symbols of emotions, foster a sense of relatability and warmth in digital communications. Research by Das et al. (2019) indicates that the incorporation of emojis in marketing communications enhances emotional expression, diminishes ambiguity, and renders the material more accessible. Research by Jaeger and Ares (2020) indicates that emojis can evoke positive emotional responses, hence enhancing customer engagement and cultivating a sense of connection with the business. Emotional responses are essential in shaping client perceptions towards products and services, hence affecting their purchasing decisions. Research conducted by Li and Xie (2022) revealed that firms incorporating emojis in their social media communications achieved elevated click-through and conversion rates, as consumers regarded these brands as more genuine and accessible. This highlights the increasing importance of emojis as a marketing instrument that may improve customer experiences and influence purchasing behaviour in the digital era.

Social media marketing has emerged as a fundamental component of contemporary digital tactics, use networks such as Facebook, Instagram, Twitter, and TikTok to link firms with customers. It is characterised as the utilisation of social media platforms to market products, services, or brands through the creation of compelling content, encouraging bilateral contact, and stimulating customer engagement. Kaplan and Haenlein (2010) assert that social media marketing enables firms to engage wider audiences at a minimal expense, providing a platform for direct, real-time interaction with consumers. This tailored engagement has demonstrated an enhancement in consumer loyalty and brand affinity. Social media marketing utilises data-driven insights to effectively target particular consumer segments, in addition to fostering participation. Research conducted by Andrew and Soontae (2020) illustrates that platforms such as Facebook and Instagram enable marketers to utilise algorithms to target potential customers according to their interests, behaviours, and demographics, hence improving the efficacy of marketing initiatives. These systems deliver insights that elucidate consumer behaviour, preferences, and trends, allowing firms to refine their marketing tactics. Moreover, social media marketing promotes user-generated content, as consumers frequently share and recommend products, so enhancing brand visibility and trust. Moreover, social media marketing amplifies brand narratives, which are essential for fostering emotional relationships with viewers. Aral (2021) asserts that firms employing narrative in their social media strategies are likely to foster more robust emotional connections with their customers, resulting in heightened buy intentions. The interactive nature of social media enables collaboration between businesses and influencers, permitting corporations to leverage the influencers' established following and credibility. Consequently, social media marketing has transformed from a simple promotional instrument into a dynamic arena where firms can cultivate consumer relationships, establish communities, and stimulate sales.

Review of Literature

Emoji marketing has become a potent instrument in digital and social media campaigns, enabling firms to express emotions and engage with customers in a more personalised and sympathetic manner. Emojis, as pictorial representations of emotions, objects, and symbols, are widely utilised in marketing to augment engagement and emotional resonance in brand communications. A new study by Li and Xie (2022) emphasises that emojis are a crucial component in digital marketing since they diminish linguistic barriers and provide a common language that appeals to varied consumers. This is especially significant in social media marketing, as rapid and succinct communication is essential for engaging people' attention. Studies indicate that incorporating emojis in marketing communications can enhance consumer perception and behaviour. A study by Pfitzner and Herring (2021) demonstrated that emojis can enhance customer engagement by infusing emotional depth into written information, hence becoming it more attractive and relevant. Emojis facilitate the humanisation of brand interactions, hence enhancing customer trust and loyalty. Furthermore, they facilitate more impactful brand storytelling by swiftly eliciting emotions and enhancing information memorability. This corresponds with the research of Diefenbach and Christoforakos (2020), which revealed that emojis can augment emotional expressiveness and engagement in online conversations, resulting in increased brand recall and purchase intention.

Furthermore, emoji marketing transcends social media postings, encompassing email marketing, push notifications, and product packaging, as firms acknowledge the efficacy of visual signals in fostering a memorable brand experience. A study by Das et al. (2021) indicated that advertisements incorporating emoticons in their messaging had heightened click-through rates and customer engagement, as emojis rendered the material more visually appealing and accessible. Nevertheless, the study cautions that excessive or improper usage of emojis may have the contrary effect, rendering a brand as unprofessional or inauthentic. Consequently, emoji marketing has demonstrated efficacy in cultivating emotional connections with consumers, augmenting engagement, and ultimately influencing purchasing behaviour. When employed wisely, emojis can assist organisations in establishing a unique and captivating digital presence.

Consumer behaviour in social media marketing is a complex phenomenon influenced by the interactive and dynamic characteristics of social networks. Social media provides brands with the capability to engage consumers instantaneously, facilitating bilateral communication that profoundly impacts purchasing choices. Social media consumers are not passive recipients; they actively engage with material, share ideas, and offer feedback, which subsequently influences their brand impressions and purchasing decisions. Wang and Yu (2020) assert that social media users demonstrate elevated brand involvement via likes, comments, and shares, frequently resulting in enhanced trust and loyalty. This interaction can create a ripple effect, as consumers significantly depend on peer evaluations, influencer endorsements, and user-generated content in their purchasing decisions. A fundamental element of consumer behaviour on social media is the impact of social influence. Aral and Walker (2021) demonstrate that consumers are more inclined to buy products endorsed by friends, family, or influencers on sites such as Instagram and TikTok. Social proof, defined as the inclination to align with the behaviours of others, significantly influences consumer purchase behaviour.

Social media enhances this phenomenon by rendering consumer experiences and reviews prominently visible and readily available, thus bolstering the credibility of companies among prospective purchasers. Besides social influence, emotional involvement is a pivotal factor in customer behaviour on social media. Kumar et al. (2021) assert that emotionally evocative information—be it humorous, motivating, or relatable—provokes more intense reactions from consumers, hence enhancing the probability of their engagement with the content and subsequent purchasing behaviour. The emotional bond is frequently augmented by visual components such as photographs, videos, and emoticons, which personalise brand encounters and cultivate more profound ties. Ultimately, targeted advertising on social media has transformed consumer behaviour by enhancing the personalisation of marketing initiatives. Platforms such as Facebook and Instagram employ advanced algorithms to present highly pertinent advertisements based on user behaviour, interests, and demographics, as noted by Andrew and Soontae (2020). This customisation enhances customer receptivity to advertisements, hence elevating the probability of conversion. Social media marketing has fundamentally altered customer behaviour by enhancing the personal, social, and emotional dimensions of brand–consumer interactions.

Research Objectives

- **To examine the role of emojis in enhancing customer purchasing behaviour** in social media marketing campaigns and how this emotional connection influences customer purchasing behavior.

Research Gap

Despite the increasing prevalence of emojis in social media marketing, a substantial study gap persists on their specific influence on consumer purchase behaviour. Although prior research has examined the emotional and communicative roles of emojis in digital interactions, there is a paucity of studies that particularly investigate the impact of these visual features on customers' decision-making processes and purchasing intentions. Current literature, including research on emotional engagement (Das et al., 2019) and brand communication (Pfitzner & Herring, 2021), predominantly examines the overarching function of emojis in augmenting engagement, yet lacks comprehensive analysis regarding the impact of various emoji types (e.g., facial, symbolic, or cultural) on purchasing behaviour among different demographic segments.

Research Methodology

The collection of quantitative data involves the analysis of various characteristics, including Brand Communication, Sales Performance, and Customer Engagement. Qualitative data are acquired through interviews with people employed in Social Media marketing businesses such as Flipkart, and Amazon. Additionally, questionnaires are administered to candidates who have had experiences with the information system. Total of approximately 200 samples have been gathered for this investigation. Data collection has taken place in Bangalore. The gathered data have been imported into IBM SPSS database for subsequent analysis, including chi-square analysis and regression analysis.

Research Model

Analysis and Interpretation

Demographic Analysis

Demographic Analysis entails the examination of particular attributes of a population, encompassing elements such as age, gender, income, educational attainment, cultural heritage, and geographic location. Demographic analysis is essential in marketing, as it enables firms to customise their tactics to address the demands and preferences of various client segments. In social media marketing, particularly regarding the influence of emojis on consumer purchasing behaviour, demographic analysis enables marketers to comprehend how various population segments respond to visual stimuli such as emojis and whether these factors affect purchasing decisions differently among groups.

The demographic profiles of the respondents were analysed using IBM SPSS using frequency analysis in Table 1.

From Table 1, the researcher found that 75% of the respondents are male falling under age group of 25–30. All the respondents' work in the private sector since the survey has been collected in industries limited to Flipkart and Amazon and around 65% of respondents have an annual income between 8 and 10 Lpa. Approximately 70% of the employees are unmarried.

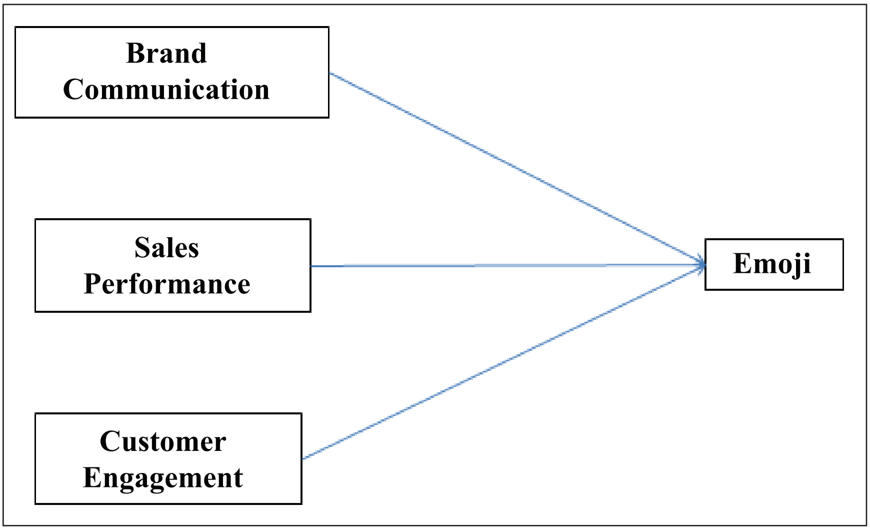


Figure 1: Factors influencing Emoji in Social Media Marketing.

Table 1. Demographic Details.

Demography Factor	Highlighting Criteria	Percentage of Response
Age	25–30	70%
Gender	Male	75%
Occupation	Private employees	100%
Annual income	8–10 Lpa	65%
Marital status	Unmarried	70%

Reliability Test

A reliability test is a statistical analysis performed to assess the consistency and stability of a measurement instrument, such as a survey or questionnaire. In studies examining the influence of emojis on consumer purchasing behaviour in social media marketing, a reliability test ascertains that the acquired data are trustworthy and suitable for deriving meaningful findings. This method entails presenting the identical survey or measurement tool to the same cohort of participants at two distinct time intervals. The correlation between the two score sets demonstrates the measurement's temporal stability. A strong correlation (often over 0.70) indicates robust test-retest reliability.

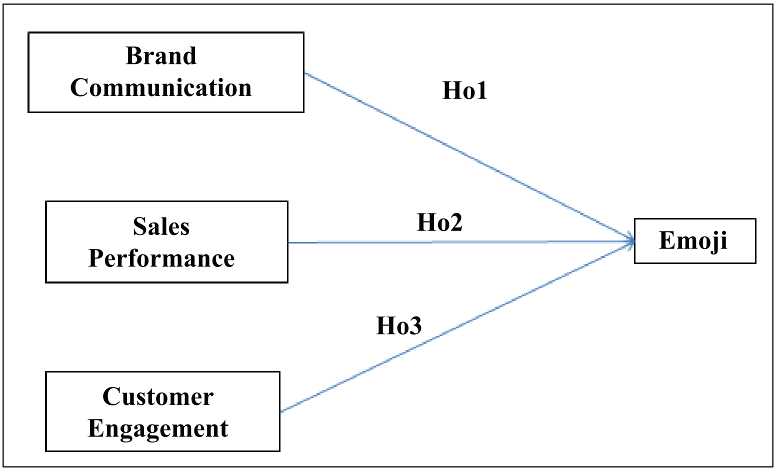
The Cronbach α Value of all the factors taken for the study are above 0.7 i.e., brand communication with Cronbach's Alpha value 0.944, sales performance with Cronbach's Alpha Value 0.960, customer engagement with Cronbach's alpha value 0.855 and emoji with Cronbach's alpha value 0.899; so all the factors are reliable for the study (Table 2).

Table 2. Reliability Test of All Variables.

Factors	Cronbach α Value	Status
Brand communication	0.944	Reliable
Sales performance	0.960	Reliable
Customer engagement	0.855	Reliable
Emoji	0.899	Reliable

Chi-square Analysis

Chi-square analysis is a statistical technique employed to ascertain whether a significant correlation exists between category variables. It assists researchers in determining whether the observed frequencies across several categories deviate from the expected frequencies under the null hypothesis, which generally posits that no link exists between the variables. Chi-Square analysis enables researchers to discern correlations between categorical data, yielding insights into consumer behaviour and preferences.



H_1: There is no significant relationship between Brand Communication and Emoji.
H_2: There is no significant relationship between Sales Performance and Emoji.
H_3: There is no significant relationship between customer engagement and Emoji.

According to Table 3, the researcher discovered that all hypotheses are significant. The p values for the full hypothesis are .000, .000, and .000, all of which are <.05. All hypotheses are examined for the study.

Model Fit Summary and Regression Analysis

Regression Analysis is a robust statistical technique employed to elucidate the relationship between a single dependent variable and one or more independent variables. In examining the influence of emojis on consumer purchase behaviour in social media marketing, regression analysis can quantify the degree to which emoji usage affects purchasing decisions while accounting for other variables. A detailed Model Fit Summary and Regression Analysis enable researchers to extract significant insights concerning the impact of emojis on consumer purchase behaviour in social media marketing.

Tables 4 and 5 provide an R square value of 0.716 at a significance level of 0.000 ($P \leq .05$). Approximately 72% of the variation was attributed to the three components, all of which were statistically significant at a significance level of 0.000 ($P \leq .05$). The results acquired validated the precision of the regression analysis in this research study; therefore, the final outcomes can be considered

Table 3. Chi-Square Test.

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson chi-square (Ho1)	484.363[a]	12	0.000
Pearson chi-square (Ho2)	425.419[a]	12	0.000
Pearson chi-square (Ho3)	137.592[a]	12	0.000

Note: adenotes 11 cells have expected count less than 5. The minimum expected count is 12.

Table 4. Model Summary.

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.846[a]	.716	.714	.392	1.856

Note: aadjacent to R typically offers more information regarding the independent variables incorporated in the regression model; boffers more information or clarifications pertinent to the model or computations. It defines the dependent variable "Emoji". It also indicates which variables are predicted in the model.

Table 5. ANOVA.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	*F*	Sig.
1	Regression	197.072	3	65.691	428.480	.000[b]
	Residual	78.189	510	.153		
	Total	275.261	513			

Note: aadjacent to R typically offers more information regarding the independent variables incorporated in the regression model; boffers more information or clarifications pertinent to the model or computations. It defines the dependent variable "Emoji". It also indicates which variables are predicted in the model.

Table 6. Regression.

		Coefficients[a]				
		Unstandardised Coefficients		Standardised Coefficients		
Model		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	.567	.114		4.970	0.000
	Brand Communication	.742	.040	.736	18.379	0.000
	Sales Performance	.101	.037	.109	2.728	0.007
	Customer Engagement	.275	.037	.292	7.368	

Note: [a]aindicates that the dependent variable predicted in the regression model is Emoji. All predictors enumerated in the table are employed to elucidate differences in this variable.

valid for presenting the findings. The Durbin-Watson value of 1.856 signifies the lack of co-linearity.

Table 6 shows that the significance value of Brand Communication, Sales Performance, and Customer Engagement are 0.000, 0.007, and 0.000 ($P \leq .05$) which shows all these three factors are having a strong influence on Emoji in E-commerce organizations using Social Media Marketing such as Flipkart and Amazon.

Managerial Implications

The significance value of Brand Communication is 0.000 ($P \leq .05$) which shows that this factor is having a strong influence on Emoji in E-commerce industry's Social Media Marketing. Given that brand communication is essential for fostering emotional connections with consumers, e-commerce managers ought to prioritise the incorporation of emojis in their social media campaigns. Emojis function as visual abbreviations that express emotions and tone, enhancing the relatability and engagement of texts. Incorporating emojis into business communications enables managers to cultivate a more accessible and amiable company image, which is crucial in a fiercely competitive market where consumer trust and loyalty are vital. The considerable importance of brand communication indicates that organisations ought to establish protocols for emoji use to maintain uniformity in brand voice across diverse platforms. This consistency reinforces brand identification and guarantees that consumers receive a unified message, irrespective of the channel. Educating marketing teams on the subtleties of emoji utilisation might augment their capacity to engage target audiences successfully. The findings suggest that e-commerce firms ought to utilise emojis to improve customer engagement. Utilising emojis in promotional materials enables firms to attract attention and enhance the probability of shares and engagements. This enhances visibility and stimulates user-generated content, since consumers are more inclined to engage with and disseminate pieces that evoke an emotional response. Ultimately, comprehending the impact of brand communication on emojis can assist organisations in customising their methods for various populations. For example, younger demographics may react more positively to innovative and whimsical emoji usage, whilst elderly consumers may favour a more restrained approach. By segmenting the audience and tailoring emoji utilisation accordingly, marketers may optimise the efficacy of their social media marketing initiatives.

A significant value of 0.007 ($P \leq .05$) for sales performance demonstrates a strong correlation between the proficient use of emojis in social media marketing and the consequent sales results in the e-commerce sector. This association has significant management ramifications that can improve marketing strategies and stimulate revenue growth. The significant impact on sales performance indicates that e-commerce managers ought to integrate emojis into their marketing messages to enhance client engagement and appeal. Emojis facilitate the expression of emotions, individuality, and brand principles, enhancing the relatability and appeal of promotional communications. Utilising emojis in product descriptions or marketing can elicit good feelings and encourage impulse purchases, hence enhancing sales. Managers ought to investigate the strategic utilisation of emojis in campaigns to augment product visibility and attract consumer attention, especially within congested social media feeds. Moreover, the results underscore the significance of tracking and evaluating customer reactions to emoji utilisation. Through A/B testing and the evaluation of engagement metrics, including click-through rates, conversion rates, and customer feedback, managers can acquire significant information regarding the influence of various emoji techniques on sales performance. This data-centric methodology facilitates ongoing enhancement of marketing strategies, permitting firms to adjust to consumer inclinations and optimise the efficacy of their social media initiatives. The importance of sales success highlights the necessity for firms to educate their marketing teams on the proficient utilisation of emojis. Effective training can enable team members to choose suitable emojis that correspond with brand messaging and appeal to the target audience. Certain emojis might express excitement or urgency, rendering them suitable for time-sensitive marketing, whilst others may signify trust and reliability, essential for fostering client loyalty. A comprehensive understanding of emoji utilisation can enhance marketing material, hence increasing sales. E-commerce managers must evaluate the demographic variables affecting emoji reception. Distinct customer segments may perceive emojis variably; hence, customising emoji usage for certain target consumers can augment its efficacy. Younger consumers may favour a whimsical and fashionable emoji aesthetic, but elderly consumers may opt for a more direct design. By tailoring emoji strategy according to demographic analytics, firms can enhance their chances of engaging with their audience and boosting sales. The correlation between emoticons and sales performance underscores the necessity for a holistic marketing approach that incorporates emojis across multiple touch points. Managers must guarantee that emoji usage is uniform throughout social media marketing, email marketing, product packaging, and customer support interactions. An integrated emoji approach can augment brand recognition and strengthen the emotional bond fostered through social media initiatives, resulting in increased customer retention and repeat purchases.

The significant value of 0.000 ($P < .05$) for customer engagement underscores a robust correlation between emoji use and the degree of consumer interaction in social media marketing within the e-commerce sector. This discovery has substantial management ramifications that can improve the efficacy of marketing initiatives and cultivate stronger relationships with customers. The significant impact of customer involvement highlights the necessity of utilising emojis to strengthen emotional bonds with consumers. Emojis are not merely visual symbols; they possess emotional significance and may express feelings swiftly and efficiently. E-commerce administrators want to contemplate including emojis into their social media content to enhance relatability and engagement of communications. Utilising emojis in posts, comments, and direct messages helps personalise the brand, rendering it more accessible and amiable. This emotional resonance can substantially enhance customer engagement, resulting in heightened likes, shares, comments, and interactions with the brand's content. The substantial correlation between customer engagement and emojis indicates that marketers can leverage emojis to develop engaging and dynamic social media campaigns. Managers ought to consider integrating emojis into polls, quizzes, and contests, as these formats promote involvement and may result in elevated engagement rates. By soliciting consumer ideas or preferences using emojis, brands may cultivate a feeling of community and promote user-generated content, thereby enhancing brand visibility and attracting new customers. The results suggest that e-commerce managers ought to examine client behaviour and preferences about emoji utilisation. Comprehending which emojis appeal most to the target demographic might enhance marketing methods. Managers could employ analytics tools to monitor engagement numbers related to various emojis in their campaigns. By discerning patterns in customer responses, firms can customise their emoji use to correspond with audience preferences, so augmenting engagement and loyalty. Moreover, the substantial impact of customer engagement underscores the imperative for organisations to sustain an active and responsive presence on social media. Interacting with customers in real time, incorporating emojis in replies, and recognising user-generated content can cultivate a reciprocal dialogue that enhances relationships. Brands that adeptly employ emojis to interact with their audience exhibit a dedication to consumer engagement, perhaps resulting in enhanced brand loyalty and favourable word-of-mouth marketing. The relationship between customer engagement and emoji utilisation underscores the necessity for a unified approach that integrates emoticons across several social media channels. E-commerce managers must ensure that emoji utilisation is congruent with the brand's identity and messaging across all platforms, fostering a consistent and recognisable presence. This consistency not only enhances brand recognition but also fosters consumer trust, hence increasing engagement.

Conclusion

Factors such as brand communication, sales performance, and customer engagement play a pivotal role in shaping the social media marketing strategies of e-commerce giants such as Flipkart and Amazon, especially in the context of emoji usage. Emojis function as effective instruments for augmenting brand communication by infusing emotional resonance and relatability into marketing messaging, rendering brands more accessible and engaging. The substantial effect of sales performance highlights that the proficient incorporation of emojis can enhance customer engagement and affect purchase choices, since emojis attract attention and communicate urgency or enthusiasm in marketing efforts. The robust correlation between customer engagement and emoji utilisation highlights that these symbols can facilitate engaging and dynamic conversations with consumers, enhancing engagement via likes, shares, and comments. Flipkart and Amazon may utilise these information to carefully include emojis into their marketing strategies, so fortifying consumer relationships, boosting sales, and augmenting their total brand visibility on social media platforms. By persistently enhancing their utilisation of emojis according to consumer preferences and engagement data, both organisations can sustain competitiveness and relevance in an increasingly digital marketplace.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Surjadeep Dutta https://orcid.org/0009-0004-4637-6844

References

Andrew, Y., & Soontae, A. (2020). Data-driven social media marketing: Insights from Facebook and Instagram advertising. *Journal of Marketing Communications*, *26*(4), 389–407.

Aral, S. (2021). *The hype machine: How social media disrupts our elections, our economy, and our health—and how we must adapt*. Harvard Business Review Press.

Aral, S., & Walker, D. (2021). Social influence and the diffusion of products in social networks. *Journal of Marketing Research*, *58*(3), 537–550.

Das, G., Jain, S. P., & Gohil, M. (2021). Visual marketing: The role of emojis in enhancing consumer engagement and sales. *Journal of Consumer Psychology*, *31*(4), 689–704.

Das, G., Pandey, N., & Kumar, R. (2019). The role of visual and verbal metaphors in enhancing the emotional appeal of advertising: Evidence from emojis. *Journal of Consumer Marketing*, *36*(3), 399–410.

Diefenbach, S., & Christoforakos, L. (2020). The psychology of emojis: A critical review of research. *Frontiers in Psychology*, *11*, 1071.

Jaeger, S. R., & Ares, G. (2020). Emotional responses to emojis in text-based marketing communication. *Food Quality and Preference*, *81*, 103848.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, *53*(1), 59–68.

Kumar, A., Bezawada, R., & Subramanian, K. (2021). Emotional engagement and consumer behavior in social media marketing. *Journal of Consumer Psychology*, *31*(3), 483–496.

Li, Y., & Xie, T. (2022). Emoji usage in social media marketing and its impact on customer engagement: A case study of brand communications. *Journal of Interactive Marketing*, *58*, 75–88.

Pfitzner, C., & Herring, S. C. (2021). The persuasive power of emojis: How emojis impact consumer attitudes and behavior in marketing communication. *Journal of Computer-Mediated Communication*, *26*(2), 75–91.

Wang, Z., & Yu, X. (2020). Social media engagement and consumer behavior: The role of trust and perceived brand value. *Journal of Business Research*, *120*, 475–486.

Article

MDIM Journal of Management
Review and Practice
3(1) 68–89, 2025

DOI: 10.1177/mjmrp.251315001
mbr.mjmrp.mdim.ac.in

From China to India: Navigating the Global Sourcing Landscape

Gursimran Kaur Ahluwalia[1] and Kanupriya[2]

Abstract

This article examines the transition of global sourcing hubs from China to India, driven by economic, political and social factors. A mixed methods approach using trade data and existing literature including relevant policies of the Government of India is employed for the purpose of analysis in this study. As per the findings of this work, the key drivers of this shift are India's competitive labour costs due to an abundant labour force, favourable government policies and improving infrastructural facilities. The study concludes that while challenges on the fronts of customs, infrastructure, international shipments, logistical quality and competence, tracking and tracing and timeliness remain, India is poised to become a major player when it comes to global sourcing. These insights are crucial for businesses and policymakers aiming to navigate the evolving landscape of global trade sourcing. In sum, challenges and opportunities linked with India's infrastructure and scalability for trade and logistics are crucial in determining its global role. As India strives to compete with China in becoming the next global sourcing hub, the importance of robust logistics and shipping networks cannot be ignored.

Keywords

China, global sourcing, India, logistical quality

Introduction

Over the past decade, China has experienced remarkable economic growth, solidifying its position as a global economic powerhouse. This period has been characterised by significant advancements in various sectors, driven by strategic

[1]Student, EPGDIB (Summer), 2023-25, IIFT Delhi
[2]Department of Economics, Indian Institute of Foreign Trade (IIFT), Delhi, India

Corresponding author:
Kanupriya, Department of Economics, Indian Institute of Foreign Trade (IIFT), Delhi 110016, India.
E-mail: Kanupriya@iift.edu

policies and robust economic planning (Atkinson & Atkinson, 2024; Shah et al., 2024).

China's industrial sector is the main contributor to its economic growth. The country is often called the *Factory of the World* as it has invested heavily in Innovation and Technology, leading to advancements in manufacturing, Artificial Intelligence and green energy. These investments have not only pushed productivity but also positioned China as a leader in high-tech industries. Many multinational companies (MNCs) rely on Chinese factories to manufacture goods, from electronics and textiles to machinery and automobiles (Atkinson & Atkinson, 2024; Deutch, 2018; Spoggi, 2020).

China's favourable government policies play a crucial role in attracting investors and getting foreign direct investment (FDI) inflows. They also incentivise businesses to expand their operations in the country promoting its overall development. The humongous labour force and extensive supplier ecosystem support the manufacturing sector, helping drive productivity, expertise and cost-effectiveness (Atkinson & Atkinson, 2024; Deutch, 2018). China's investment in its physical infrastructure in the form of highways, railways and ports provides a boost to its domestic and trade development and builds its reputation, domestically as well as internationally (Atkinson & Atkinson, 2024; Deutch, 2018).

However, recently, due to the pandemic and the growing economic tensions between the US and China, many businesses are reconsidering their reliance on Chinese suppliers and diversifying their supply chains. This has given rise to *China-plus-one* strategy. As a result, there is growing interest in finding alternative sourcing options with India emerging as a potential replacement for China (Lazard, 2024).

The primary objective of this article is to assess India's potential as an alternative to China for global sourcing driven by socio-economic and political factors. Past literature has mainly focused on the competitiveness of other developed economies. While some studies touch upon India's potential; none systematically compares the country's viability as a sourcing alternative to China.

This article is divided into the following sections. First, an introduction to the research topic is given. Second, a thematic review of literature is conducted, centred around the PESTEL (Political, Economic, Social, Technological, Environmental and Legal) framework. Third, the methodology of this study is explained. Last, conclusion and future policy implications of this work are explicated.

The next section reviews existing literature within a PESTEL framework.

Review of Literature

According to Balu et al. (2022), global sourcing can only be applied to highly standardised parts and components in manufacturing.

Innovations in global supply chains have emerged as critical contributors to flexibility and competitive strength, ultimately leading to beneficial impacts for the firm, industry, and nation (Dolgui & Ivanova, 2017). China is at the forefront of adopting automation and robotics in its manufacturing processes. From advanced robotic assembly lines to automated warehouses, these technologies infuse efficiency, precision and productivity in the supply chains (Zhao, 2023).

Recently, India's rise as a viable global sourcing alternative to China has attracted considerable interest. This transition is driven by several factors which could include better competitive pricing, a youthful and skilled labour force and a benign business climate for foreign investors. Moreover, India's unique path to integration with the global markets, characterised by limited FDI yet, significant growth in textile and apparel exports, highlights the importance of domestic policy changes and evolving demand structures being the key factors in the country's emergence as competitive sourcing hub (Madhani, 2008).

Evolving Global Dynamics

The global landscape has undergone significant transformations over the past few years. The collapse of the Soviet Union led to the rise of the United States as the sole superpower, but China's recent ascent is moving the world towards multi-polarity. Its economic prowess, technological advancements and global influence have positioned it as a major force (Brooks & Wohlforth, 2015).

Simultaneously, Southeast Asia has also witnessed remarkable growth, with countries like Singapore and Vietnam becoming key players in the global economy. India too, has emerged as a prominent player, driven by its expanding economy, large population and diplomatic initiatives (HSBC, 2024).

The ongoing Ukraine-Russia conflict highlights the geopolitical complexities of the modern world. In response to these dynamics, many MNCs are adopting a *China-plus-One* strategy, diversifying their supply chains to reduce reliance on any single country. This strategy has placed India in the spotlight as an attractive alternative sourcing destination. India's competitive labour costs, skilled workforce and improving business environment make it a compelling choice for companies seeking to diversify their sourcing strategies (Lazard, 2024).

Labour Cost Analysis: China Versus India

Steep Increase in China's Manufacturing Costs

China's decades-long reign as the 'world's factory' is facing headwinds due to escalating manufacturing costs, raising challenges for businesses in that country and altering the global manufacturing landscape. Several factors contribute to these rising costs. Significant wage growth for Chinese workers over the past decade is one. Another is a shrinking labour pool due to an ageing population and declining birth rates. Additionally, increasing cost of raw materials and other inputs is also driving up manufacturing costs (Atkinson & Atkinson, 2024; Lazard, 2024).

The rise in manufacturing costs in China has had various implications for businesses. Some firms have relocated their operations to countries with lower labour costs, notably, those in Southeast Asia. Others have invested in automation and advanced technologies to boost productivity and reduce dependence on manual labour. Some have passed higher costs to customers through increased prices. The Chinese government is aware of the challenges posed by rising manufacturing costs and is taking steps to address them. These measures include policies to promote technological innovations, skill development and economic restructuring (Global Data, 2024; Lazard, 2024).

The future of manufacturing in China remains uncertain. However, it is evident that the country's low-cost advantage is no longer as strong as it once was. Businesses operating in China will need to adapt to the changing landscape to stay competitive.

The issue of rising labour costs in China is complex and multifaceted, with both positive and negative implications. Labour costs have increased for the period 2010–2021 (Figure 1).

Some of the key reasons for rising labour costs in China are first, wage growth and improved standard of living. One of the primary causes of increasing labour costs in China is the significant wage growth experienced by workers over the past decade. Higher wages contribute to an improved standard of living for Chinese workers, allowing them to afford better housing, healthcare, education and consumer goods. Second, shrinking labour pool. China's labour force is gradually shrinking due to factors such as an ageing population, declining birth rates and urbanisation. As the supply of available workers decreases, employers are compelled to offer higher wages to attract and retain talent. This scarcity of labour has played a major role in driving up labour costs. Third, increased regulatory burden. China has implemented stricter environmental regulations and labour laws in recent years. While helpful for sustainability and worker well-being, these measures often translate into higher compliance costs for manufacturers. Fourth, land and energy costs. Rapid industrialisation has led to increased competition for land and resources, driving up their prices. Manufacturing hubs, particularly in coastal areas, face soaring land costs, impacting factory operations. Similarly, energy prices have risen, adding to overall production expenses. All in all, higher labour costs in China can pose challenges for businesses, particularly small and medium-sized enterprises (SMEs) that rely heavily on low-cost manufacturing. Some companies may struggle to maintain profitability and could consider diversifying their supply chains or moving operations to countries with lower labour costs (Global Data, 2024; Yang et al., 2010; Zhang et al., 2023).

India's Competitive Edge: Cheap and Abundant Labour

India's supply of inexpensive labour has long been a key attraction for global businesses. The same is on account of the country's huge population, mainly consisting of young people with diverse skill sets. This *demographic dividend* results in a vast workforce available at low labour costs as compared to other countries. Furthermore, India's labour market is characterised by a mix of low and semi-skilled workers and highly educated professionals. With a growing focus on education, the country is blessed with a skilled workforce in various fields such as technology, engineering and services. The sheer variety offered by a differently skilled workforce allows businesses to choose labour that best fits their specific needs and budget constraints. An accessible and affordable labour force has encouraged many MNCs to outsource some of their business operations to India. However, while India's labour remains cost-effective, it is important to consider other factors such as infrastructure, logistics, regulatory environment and market access when making investment decisions in the complex global business landscape. Some of these could be elaborated as follows. First, demographic advantage is offered by a large and expanding population, with a notable portion of its workforce being young and relatively low-skilled. This demographic benefit results in a vast pool of labour. Second, wage disparity is another area of concern. There are significant wage differentials between urban and rural areas in India, as well as across regions. Labour costs are generally lower in rural areas where the cost of living is lower. This wage disparity makes it appealing for businesses to utilise relatively inexpensive labour available in rural parts of the country. Third, the Government of India (GOI) has introduced several initiatives and reforms to boost labour-intensive sectors and draw foreign investments. Programmes such as *Make in India* are designed to strengthen the manufacturing sector and create job opportunities in the same. These efforts, along with supportive policies and tax incentives, help ensure the availability of affordable labour in the country (IBEF, 2024a; Raman, 2016) (Figures 2 and 3).

PESTEL Analysis

PESTEL analysis studies the macroeconomic framework external to the firm (s) (Buye, 2021; Christodoulou & Cullinane, 2019; Debourdeau et al., 2021). It is a diagnostic tool for strategic business planning that provides a tactical framework for understanding the exterior influences on a business entity. It is used by firms for evaluation of the impact that the outside environment might have on a project. It groups external factors into various classifications under the broad headings of PESTEL considerations. It is one of the most sought-after tools of investigation used in strategic management (Christodoulou & Cullinane, 2019).

Political Analysis for India

India, recognised as a secular democratic republic, has exhibited significant political stability, especially in recent years. Political stability is one of the cornerstones of economic strength. The present administration is supportive of its industrial growth and aspires to elevate its exports to USD 2 trillion, exceeding half of the current GDP of USD 3.5 trillion. A range of initiatives, such as *Make in India* and *Production Linked Incentive* (PLI) schemes have been launched so as to enhance the production and export capabilities of domestic manufacturing firms. As a result of political stability, trade and investment policies are also favourable, with the GOI allowing up to 100% FDI in several industries.

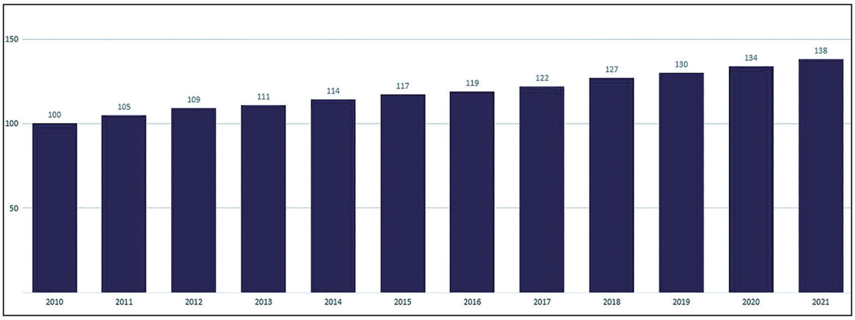


Figure 1. Labor Cost Index of China (2010–2021, Base Year 2010 = 100).

Source: Global Data (2024).

Import tariffs and export incentives are periodically reviewed to align with both current trends and future goals. *Ease of Doing Business* is another important indicator and India has been improving its position over the years, thanks to a stable political and regulatory environment. As indicated in Figure 4, India's political stability has grown over the last decade though it is still below the global average of −0.07 (IBEF, 2024b; Mitra, 2017).

Economic Analysis for India

The economy is another important component of PESTEL analysis. It is even more important given that India is one of the largest economies in the world in terms of nominal GDP. In line with this, it is one of India's foremost ambitions to promote itself as a global manufacturing and export hub.

The country also stands out as the most promising economy among developing nations with bright future prospects. With a growing labour force and rising per capita incomes, the Indian economy is set to expand over the next 30 to 50 years. This creates a compelling reason for industries to establish factories in India, furthering both domestic and export markets. A number of schemes have been introduced in this regard. First, the PLI Scheme. This scheme provides financial incentives to companies that invest in manufacturing in India. The PLI scheme has been particularly successful in the electronics sector, where it has helped attract major global companies such as Apple and Samsung. Second, the Export Promotion Councils (EPCs) are government bodies that provide support to exporters in a variety of sectors. The EPCs offer a range of services, such as market research, training and export finance. Third, the Export-Import Bank of India (EXIM Bank) provides financial assistance to exporters, such as loans and guarantees. EXIM Bank also offers export insurance, which can protect exporters from the risk of non-payment. These are just some of the initiatives that the GOI is taking to boost exports. With these initiatives in place, India is well-positioned to achieve its goal of becoming a USD 1 trillion export economy by 2030 (Varghese, 2018; World Bank, 2024a).

Social Analysis for India

Social context is another complex and diverse component of PESTEL analysis. India's societal environment is multifaceted and varied (with several religious, caste and ethnic groups) but it has some key characteristics that could help to augment its economic conditions. First, a large and expanding middle class, which is expected to reach 500 million by 2025. This social group is vital in so far it has increasing disposable incomes to spend on goods and services, giving a boost to the national GDP. Second, a young and educated workforce is an asset as the export sector is adaptable to new technologies and processes and proficient in English, the language of international trade. Third, a younger population compared to China, with a median age of 28, compared to China's 39. India has a larger proportion of its population in the working-age bracket (15–64 years old). These bode well for the nation's economic prosperity. As evident in Figures 2 and 3, in terms of literacy and labour force participation, India lags behind China on several key social parameters (Chandrasekhar et al., 2006; Ministry of External Affairs, GOI, 2021; Singh & Paliwal, 2015).

Technological Analysis for India

India's technological landscape is evolving rapidly with an emphasis on innovation and entrepreneurship. This innovative spirit is boosted by the presence of several top-tier universities and research institutions in the country. It serves as a significant centre for IT and software development. India has established itself as a global technology centre, drawing substantial investments from major tech companies such as Amazon, Apple, Meta and Google. The nation is well known

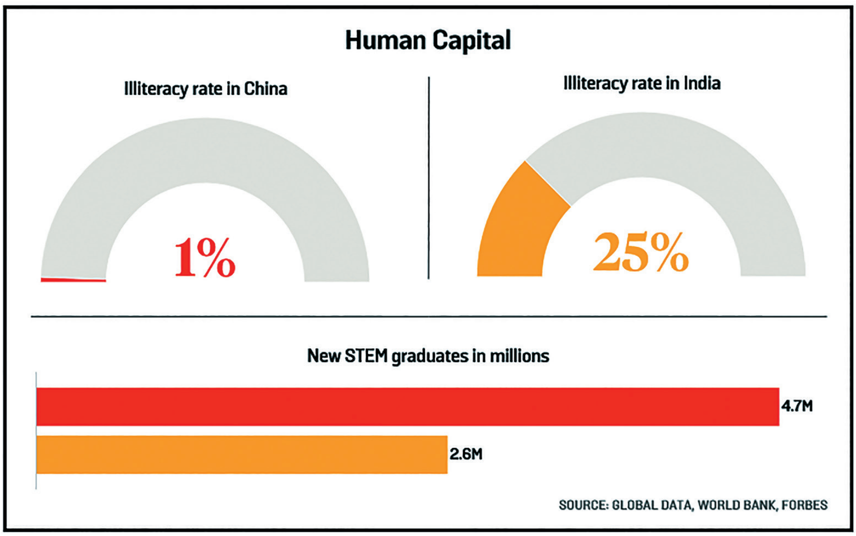


Figure 2. Human Capital.

Source: Foreign Policy (2023).

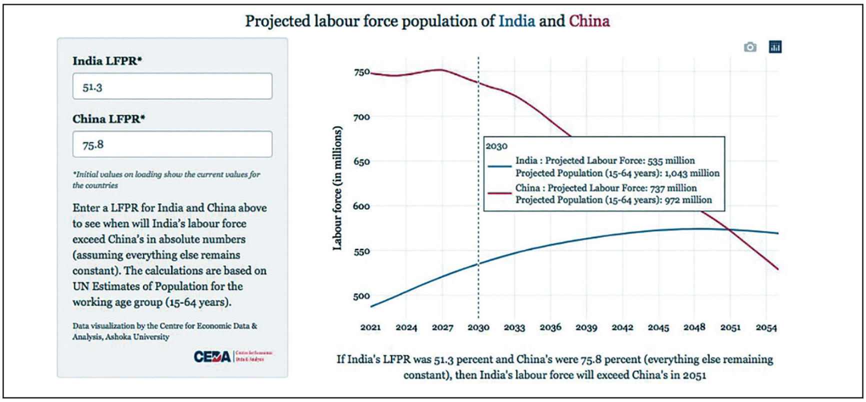


Figure 3. Projected Labour Force Population of India and China.

Source: International Economic Association (2024).

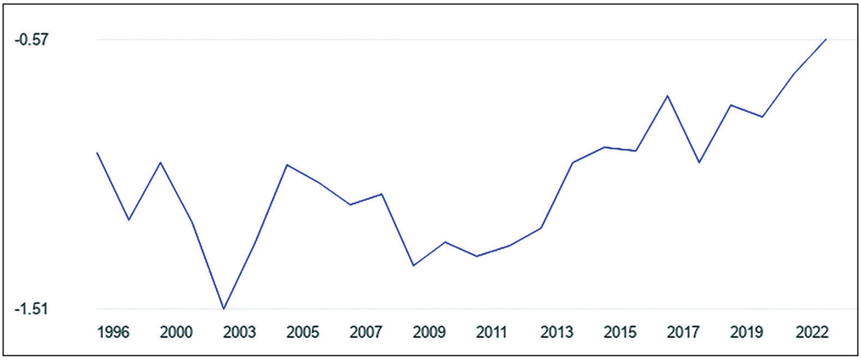


Figure 4. Political Stability Index for India (−2.5 Weak; 2.5 Strong).

Source: The Global Economy.com (2024).

for its strong IT services industry which plays a crucial role in its economic growth (Jain & Roy, 2024).

There are numerous advantages of having a strong IT and ITES infrastructure. First, IT and software development is one of India's key fortes. The country is already a key player in this domain and the sector is expected to develop further. India could enhance its expertise in cloud computing, artificial intelligence and machine learning. Second, electronics manufacturing is another area requiring attention from the policymakers. The country's electronics manufacturing industry is on the rise and is anticipated to attract greater investments. The focus is on enhancing capabilities in consumer electronics, telecommunications equipment and medical devices sectors.

Third, life science is another domain where India has a robust presence. The same is projected to grow with time. The country is already concentrating on building expertise in pharmaceuticals, biotechnology and medical devices (Jain & Roy, 2024; Jena, 2024).

Environmental Analysis for India

Apart from political, economic, social and technological analyses, a thorough environmental exploration is essential. There is a need to understand the significant interplay between a nation's growth and the broader ecological factors influencing its path. The PESTEL approach, which includes PESTEL dimensions, provides a structured method of uncovering the various forces impacting India's development. India is leveraging environmentally friendly policies to boost its exports in several ways. First, investing in renewable energy. As a leading investor in renewable energy, India is positively impacting its exports of solar panels, wind turbines and other renewable energy equipment. Second, promoting energy efficiency. By enhancing energy efficiency in the manufacturing sector, India is trying to reduce its pollution and make its products globally competitive. Third, developing environmental technologies. India is creating various eco-friendly technologies, such as pollution control equipment and water treatment systems, which are in high demand internationally and are helpful for boosting its exports (Manigandan et al., 2024).

India is often viewed as having superior ecological policies compared to China. While China has struggled with slow regulatory implementation, India is recognised for its more progressive environmental policies and a government dedicated to reducing pollution and promoting sustainable development as a policy objective. Nonetheless, India's environmental policies still require improvement. The government must strengthen the enforcement of environmental regulations and invest more in conservational infrastructure. By continuing to improve these policies, India can position itself as a leading consumer, producer and exporter of environmental goods and services. Some of these ecologically friendly policies could be discussed here. The *National Solar Mission* has fostered a dynamic market for solar panels and other renewable energy equipment. In 2020, India's solar exports reached USD 2.5 Billion. The *Energy Efficiency Labelling Programme* has reduced energy consumption in the manufacturing sector, making domestic products more globally competitive and creating new export opportunities for energy-efficient products. The *Development of Environmental Technologies* (*DET*) *Programme* is advancing new technologies like pollution control equipment and water treatment systems, which are in high demand internationally and are enhancing India's production and export capabilities (Quitzow, 2015).

Legal Analysis for India

India is blessed with a robust legal system. Its characteristics could be listed as follows. First, *stable and predictable legal system*. India's long-standing common law tradition offers businesses a reliable legal framework, unlike China's more opaque system which can change unpredictably. Second, *strong intellectual property protection*. India has robust laws for protecting intellectual property, including patents, trademarks, and copyrights, making it attractive for tech companies and others reliant on IP. Third, *increasing free trade agreements*. India has signed numerous free trade agreements, reducing tariffs and trade barriers, thus facilitating easier export of goods and services. Fourth, *Transparent Legal System*. Indian legal system's transparency helps businesses understand their rights and obligations more clearly compared to China's. Fifth, *Independent Judiciary*. India's judiciary is more independent, reducing the risk of arbitrary governance and cultivating a more welcoming attitude towards foreign investment than the Chinese government. This makes it easier for businesses to set up and operate in India (Rana & Joshi, 2022; Srikrishna, 2008).

To sum up, this PESTEL analysis highlights the complex relationship between India's growth and its surrounding environmental factors. Politically, India is a stable and vibrant democracy with a slew of pro-industry policies and initiatives of the likes of *Make in India* that may have a positive impact on the country's industrial growth and exports. Economically, a growing labour force and government schemes like the PLI and socially, a rising middle class, a young and educated workforce and a demographic dividend provide a strong base for economic growth. Technologically, India's vibrant innovation ecosystem and skilled workforce position it well for technology exports. In addition, a stable legal system, intellectual property protection and a pro-business environment strengthen export-oriented industries. Environmentally, a focus on sustainability and environmental technologies supports cleaner exports. These insights help stakeholders navigate India's diverse landscape effectively as it seeks to balance growth and tradition.

Economic Dissimilarities Between India And China

In the ever-evolving field of international business, analysing India's trade with China is of utmost importance. The same provides a deeper look at the trade dynamics between these two major economies, highlighting significant trends, patterns and insights that define their bilateral trade relations. By examining the complexities of their commercial exchanges, this segment cements the contrast between India's and China's economic status.

India's Role in the Global Economy

India's rising exports in goods and services highlight its growing role in the global economy, showcasing the competitiveness and appeal of Indian products and services in international markets. In recent years, the country has diversified its export portfolio. Traditional sectors like textiles, garments and pharmaceuticals remain key contributors, but there has been substantial growth in other domains such as IT services, software development and business process outsourcing (BPO). The country's skilled workforce, technological expertise and cost advantages have been crucial in driving the expansion of these areas (Mishra, 2024).

Additionally, GOI initiatives like *Make in India* and the *Services Exports from India Scheme* have bolstered manufacturing–driven export growth. These programmes aim at enhancing India's industrial capabilities and supporting the global expansion of its service-oriented sectors such as IT, healthcare and professional services. However, to fully realise the potential of India's exports, challenges like limitations in infrastructure, complex regulatory processes and skill gaps must be addressed. Ongoing investments in infrastructure, regulatory simplifications and skill development programmes will be essential in sustaining this growth trajectory. Figures 5–7 explain the continuously rising trend of India's exports, especially, after the post-Covid recovery in the global supply chains (Mishra, 2024).

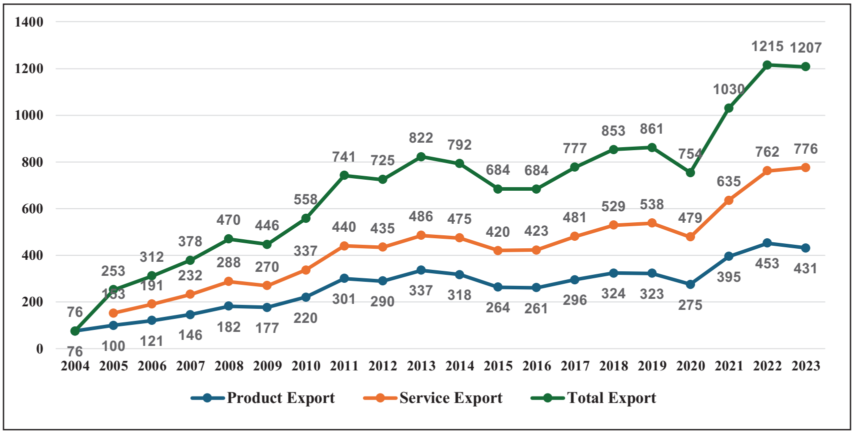


Figure 5. India's Export Trend (in Billion Dollars).

Source: ITC Trade Map (2024).

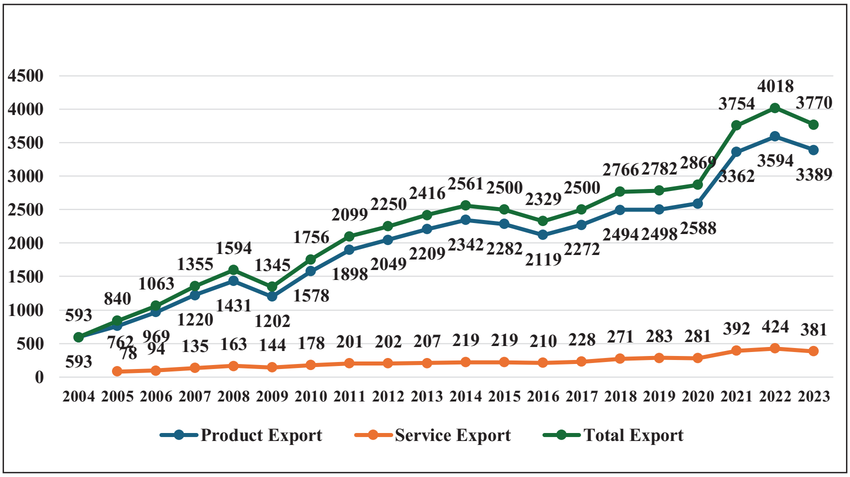


Figure 6. China's Export Trend (in Billion Dollars).

Source: ITC Trade Map (2024).

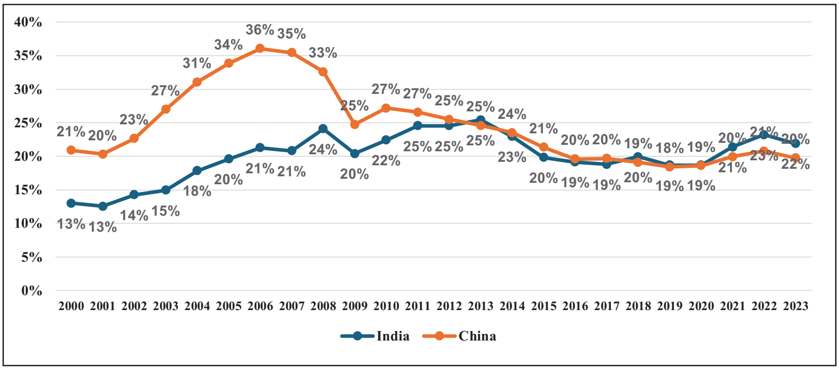


Figure 7. Exports as Percentage (%) of India's and China's GDP.

Source: ITC Trade Map (2024).

Figure 5 shows India's exports of goods and services in Billions of US Dollars.

The rise in India's exports could be attributable to the following. First, the rise of India's manufacturing sector. India's manufacturing sector has seen rapid growth in recent years, leading to increased production of exportable goods such as textiles, pharmaceuticals and engineering products. Second, growing demand for Indian goods in global markets. The demand for Indian goods has been rising globally due to factors like increasing affluence of consumers in developing countries, the growing popularity of Indian brands and a heightened focus on sustainability in global supply chains. Third, government's focus on exports. The GOI has prioritised boosting exports through various measures, including providing incentives to exporters, signing free trade agreements and promoting the use of Indian ports as transhipment hubs (IBEF, 2024a; Mishra, 2024).

China's Role in the Global Economy

Just like India, China too has experienced continuous growth in its exports, with its export volume being five times that of India over the past two decades. A key difference is that India's exports have a higher proportion of services, whereas China's growth is primarily driven by manufactured goods. China's GDP growth rate has consistently outpaced India's over the past few decades. However, India's GDP growth rate has been catching up recently and in 2021, it surpassed China's for the first time since 1990. Several factors contribute to the differences in GDP growth rates between the two countries. *First*, China's economic reforms. Initiated in the late 1970s, these reforms spurred rapid economic growth by opening the economy to foreign investment, privatising state-owned enterprises and deregulating markets. *Second*, India's economic reforms. Although India began its economic reforms in the early 1990s, these changes have been more gradual compared to China's. India has also faced challenges such as corruption and infrastructural bottlenecks. *Third*, India's demographics. With a young and growing population, India has significant potential for economic growth. However, high levels of poverty can impede this growth. *Fourth*, China's demographics.

An ageing population poses challenges for China, but the country benefits from a large pool of skilled workers, which supports sustained economic growth. It is too early to say whether India's GDP growth rate will continue to catch up to China's GDP growth rate. However, India has a number of strengths, such as a young population and a large market, which could help it achieve sustained economic growth in the years to come (Bukhari et al., 2024).

Exports as a percentage of GDP for both India and China have hovered around 20%, which is an ideal number for any economy. This indicates strong domestic consumption, helping both countries manage their vulnerabilities on account of external shocks and maintain a balanced dependence on foreign markets (ITC Trade Map, 2024).

In conclusion, India's transformative journey in global exports highlights its economic dynamism and potential. The diversification of its export portfolio, driven by technological prowess and skilled labour force, demonstrates India's adaptability to changing market demands. While initiatives like *Make in India* enhance its manufacturing prowess, addressing challenges such as infrastructural bottlenecks is crucial for sustained growth.

Comparing India's trade with China reveals distinct economic trajectories. China's manufacturing strength contrasts with India's service-oriented growth, with both nations facing unique challenges. The evolving trade dynamics necessitate careful consideration of geopolitical, regulatory and environmental factors. As India seeks to position itself on the global stage, a balance of proactive policy measures, infrastructural improvements and innovative strategies will be the key.

Policies Related to Infrastructure and Scalability

To compete with China and become a leading global sourcing destination, India must rapidly augment its trade and logistics infrastructure. This section examines India's efforts to improve its trade and logistical capabilities to rival global leaders like China. In a highly competitive landscape, India's goal to match China's infrastructural strength is a significant motivator for transformation. It is essential to discuss the Logistics Performance Index (LPI), a key benchmark developed by the World Bank to evaluate trade-related infrastructure. The LPI assesses logistics *friendliness* through six dimensions, namely, customs, infrastructure, international shipments, logistics quality and competence, tracking and tracing and, timeliness. Another important measure is the Liner Shipping Connectivity Index (LSCI), which evaluates a country's integration into the global liner shipping networks. By tracing India's progress from modest LSCI scores to nearly 60; this segment highlights improvements in maritime connectivity driven by economic growth, port expansion and new shipping lines. This segment also explores strategic initiatives like the *Pradhan Mantri Gati Shakti (PM Gati Shakti) Yojana* and the *National Logistics Policy (NLP)*, which are propelling India's rise on these fronts. Finally, it examines the transformative potential of the *Maritime India Vision 2030,* detailing its promises of increased trade and investment, job creation and enhanced economic growth. If realised, these benefits could significantly reshape India's maritime landscape and global trade influence (Kumar & Singh, 2022).

Logistics Performance Index

The LPI is an interactive benchmarking tool created by the World Bank to help countries identify challenges and opportunities they face in their performance on trade logistics and what they can do to improve the same. The LPI is based on a survey of international logistics professionals on the ground (global freight forwarders and express carriers), providing feedback on the logistics *friendliness* of the countries with which they trade. The survey covers six dimensions of logistics performance listed below. Each dimension is scored on a scale of 1 to 5, with 1 being the lowest score and 5 being the highest score. The overall LPI score is calculated as the average of the scores for the six dimensions as follows. Customs, Infrastructure, International shipments, Logistical quality and competence, Tracking and tracing, and Timeliness (World Bank, 2024b).

The LPI is an essential tool for countries aiming at enhancing their logistics performance. By identifying strengths and weaknesses across various dimensions, countries can pinpoint areas needing improvement. The LPI also serves as a benchmark for tracking progress over time. In the 2023 LPI, Singapore ranked first, followed by Denmark, Germany, the Netherlands and Hong Kong. India improved its position to 38th, climbing six places from the previous year (World Bank, 2024b) (Figures 8 and 9).

It is evident from Table 1 that India has grown significantly from 2.90 in 2007 to 3.40 in 2023 as far as its LPI performance is concerned (Table 1). In order to be successful in growing as an export hub, India should be near China in this index for which it needs to work on all aspects of this index. China's LPI rank is 19 and its score is 3.7 (World Bank, 2024b).

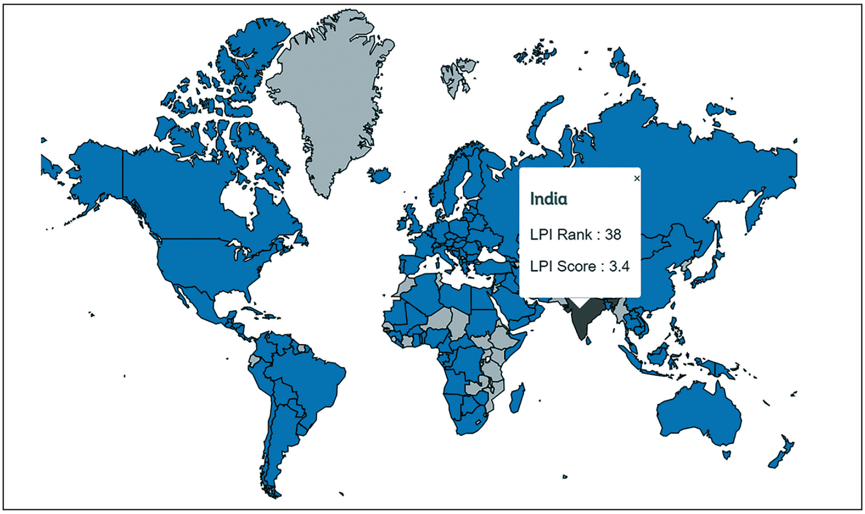


Figure 8. India's LPI Rank and Score.

Source: World Bank (2024b).

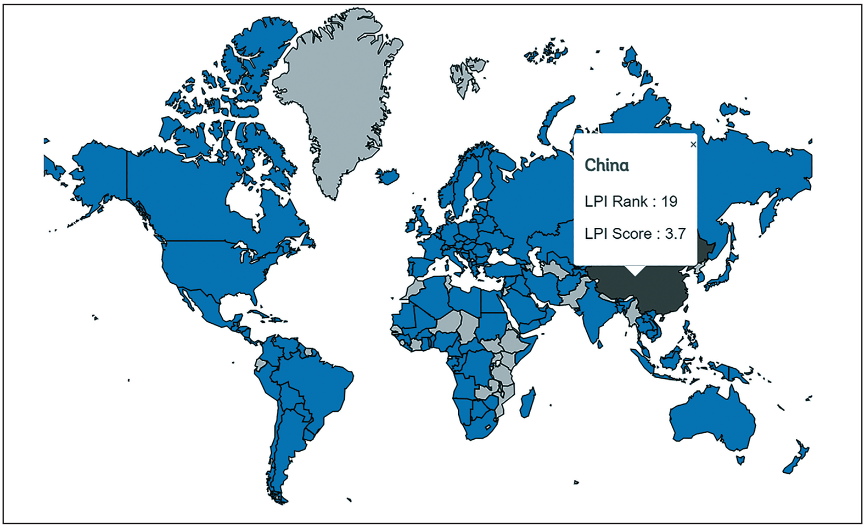


Figure 9. China's LPI Rank and Score.

Source: World Bank (2024b).

Table 1. LPI of India Versus China for the Years 2018 and 2023.

Country Name	2007	2010	2012	2014	2016	2018	2023
India	2.90	2.91	2.87	2.88	3.34	2.91	3.40
China	3.20	3.54	3.61	3.67	3.75	3.75	3.70

Source: World Bank (2024b).

Liner Shipping Connectivity Index

The LSCI gauges how well a country or port is integrated into the global liner shipping networks. There are five key components of the LSCI. Number of ships, their container carrying capacity, the maximum vessel size, the number of services and the number of companies deploying container ships in a country's ports. The LSCI is a dimensionless measure, with a baseline value of 100 assigned to the country with the highest average index in 2004. Countries with higher LSCI scores are more integrated into the global liner shipping networks, providing them with better access to global markets. The LSCI can be utilised to compare the connectivity of different countries or ports, track changes in connectivity over time and identify countries or ports that may be underserved by the global liner shipping networks. The LSCI is a crucial tool for understanding the role of liner shipping in global trade and for formulating policies to enhance ports. By analysing the LSCI, policymakers can make informed decisions to improve the efficiency of the global supply chains and foster economic development. A comparison of the LSCI for various countries, including India and China, with

Table 2. Liner Shipping Connectivity Index.

Liner Shipping Connectivity Index (Maximum Value in 2004 = 100)				
Year	China	India	Vietnam	USA
2018	153.4	55.5	66.8	92.05
2019	158.6	54.3	61.4	95.62
2020	162.4	57.2	79.8	103.85
2021	171.2	58.9	77.5	102.61

Source: UNCTAD (2024).

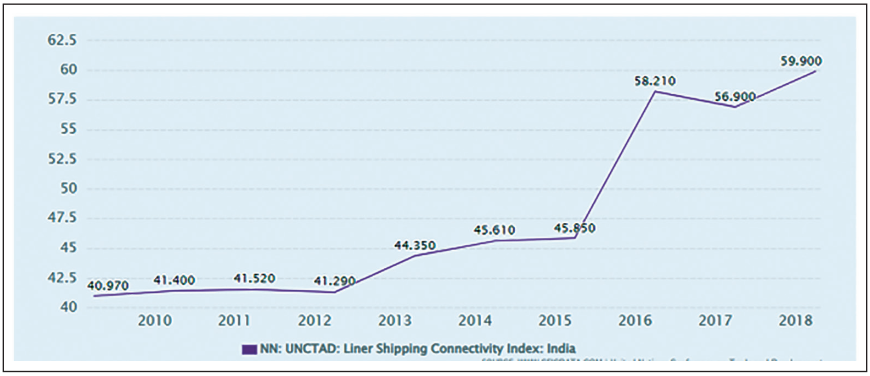


Figure 10. Liner Shipping Connectivity Index.

Source: CEIC (2024).

benchmarks against Vietnam and the USA, reveals that India's LSCI is consistently lower than China's. This indicates a significant challenge for India in achieving smooth sea connectivity to major global trade hubs (UNCTAD, 2024) (Table 2 and Figure 10).

Of late, India is improving its standing on the LSCI, thanks to GOI measures aimed at promoting free and fair trade and some factors as listed. First, *Economic Growth*. India's expanding economy has increased the demand for imported goods. Second, *Port Expansion*. The development of Indian ports has facilitated easier access for ships. Last, *New Shipping Lines*. The introduction of new shipping routes serving India (UNCTAD, 2024).

The improvement in India's LSCI is beneficial for the country's economy, providing Indian businesses with better access to global markets, which can boost trade and investment. Additionally, it offers Indian consumers a wider range of imported goods (UNCTAD, 2024).

However, there is still room for improvement. India's LSCI remains lower than that of some other countries, such as China and Vietnam, indicating potential for further enhancement in shipping connectivity (UNCTAD, 2024).

PM Gati Shakti Initiative

The *PM Gati Shakti* Yojana, launched by the GOI in October 2021, is a national infrastructure master plan aimed at integrating the planning and execution of infrastructural connectivity projects across the country. It seeks to enhance coordination among various ministries involved in these projects. Key features of the *PM Gati Shakti Yojana* include the following. First, digital platform. This platform will unite 16 ministries, including those responsible for railways, roadways and waterways, providing a single window for planning, execution and monitoring of infrastructure projects. Second**,** multi-modal connectivity. The plan emphasises developing multi-modal connectivity to facilitate seamless movement of people and goods across different transport modes, thereby, reducing logistics costs and improving economic efficiency. Third, project prioritisation. By fostering cross-sectoral interactions, the plan will prioritise projects and minimise implementation overlaps, ensuring that the most critical projects are addressed first. Fourth, transparency and accountability. The plan aims to enhance transparency and accountability in infrastructure project implementation through digital platforms and by involving all stakeholders in the decision-making process (India.Gov.in, 2024).

National Logistics Policy

In 2022, the Prime Minister launched the *NLP* to improve last-mile delivery, tackle transportation challenges, save time and resources for the manufacturing sector and achieve optimal speed in logistics. The NLP is a governmental framework introduced in 2022, aiming to enhance the logistics sector in India by making it more efficient, affordable and sustainable. The policy focuses on certain key areas. First, Infrastructure. The policy seeks to enhance logistics infrastructure, including roads, railways, ports, and airports. Second, Technology. It aims to leverage technology, such as blockchain and artificial intelligence, to boost logistics efficiency. Third, Regulation. The policy focuses on simplifying and streamlining logistics regulations, including customs clearance and cross border trade. Fourth, Skills. It aims to develop skills of the logistics workforce, including drivers, warehouse workers and IT professionals. Fifth, Finance. The policy intends to facilitate easier financing for logistics projects through loans and guarantees. Sixth, Sustainability. It aims to make the logistics sector more sustainable by reducing emissions and using recycled materials. Seventh, Collaboration. The policy promotes better collaboration among various stakeholders in the logistics sector, including government agencies, businesses and industry associations. Last, Ease of Doing Business. It aims at simplifying procedures and reducing paperwork to make logistics operations easier for businesses in India (Invest India, 2022).

Maritime India Vision 2030

The GOI has initiated efforts to improve the country's ranking and ease of doing trade through the *Maritime India Vision 2030*. The Maritime India Vision 2030 is a bold initiative with the potential to revolutionise India's maritime sector. If successful, it could significantly enhance trade and investment, generate employment and stimulate economic growth. Some of the key benefits of *Maritime India Vision 2030* could be listed as follows. First, Boost in Trade and Investment. By enhancing India's connectivity with the global maritime network, the MIV 2030 could facilitate easier import and export of goods, leading to increased economic growth. Second, Job Creation. The initiative could create numerous jobs in the maritime sector, including positions in ports, shipping and shipbuilding, thereby, boosting employment and reducing poverty. Third, Economic Growth. By making India more competitive in the global maritime markets, the MIV 2030 could attract more foreign investment and increase trade, contributing to higher economic growth (PIB, 2024).

Methodology

This thematic review of the literature study analyses existing work on transitioning global sourcing hubs from China to India. This article relies primarily upon academic databases, search engines and websites of the likes of Google Scholar, ProQuest, EBSCO Host, Web of Science and Research Gate to extract relevant studies for the theme. Besides, reports by relevant Departments/Ministries of the GOI and NGOs were also searched and used for the purpose. The same added a practical dimension to the usual academic rigour of this study; significant for gaining a comprehensive understanding of the theme. A total of 50 reference materials, including research papers, reports and websites have been used in this analysis. The main criteria for selecting the same is their relevance for the theme of this study in line with its primary research objective. To obtain as many pertinent articles as possible, this study makes extensive use of key words appropriate for the same. Some of them are being mentioned as follows. The *first group* of key words is related to the evolving global dynamics in a global context. The *second collection* of important words is relevant for India's and China's labour cost analysis in terms of an abundance of cheap labour. The *third group* pertains to the PESTEL analysis for India's and China's economies, keeping in view their political, commercial, social, technological, ecological and legal dimensions. Some of the relevant keywords are 'global sourcing', 'PESTEL', 'NLP', 'Trends in India's and China's exports and imports'. Furthermore, the theme on 'economic differences between India and China' is identified with the help of important words such as 'India's role in the global economy' and 'China's role in the global economy'. The last subject on 'Policies on infrastructure and scalability' is assessed with the help of words of the likes of 'LPI', 'LSCI', 'NLP', 'Maritime India Vision 2030' and 'PM Gati Shakti' initiative.

The ensuing chart summarises the conceptual framework followed in this study for analysis (Figure 11).

All in all, this study seeks to explore the transition of the global sourcing hub from China to India, driven by economic, political and social factors. The same aims to answer questions about whether India is overtaking China as a global sourcing hub, thereby, marking a paradigm shift in international trade logistics.

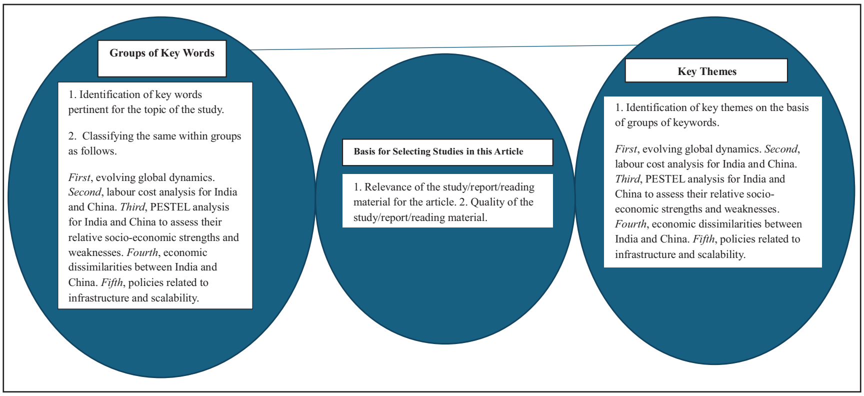


Figure 11. Flowchart for Methodology.

The subsequent section expounds the results and discussion for this article based on the analysis conducted thus far.

Results and Discussion

The main finding of this review article is the transitioning global sourcing hub from China to India in international logistics. The same is largely due to India's competitive labour costs, thanks to an abundant labour force, favourable government policies and improving infrastructural facilities. The study concludes that while challenges on the fronts of customs, infrastructure, international shipments, logistical quality and competence, tracking and tracing and timeliness remain, India is poised to become a major player when it comes to global sourcing. Further research on the theme requires primary survey analysis of major stakeholders in international trade logistics. This could render more meaningful comparisons feasible. The next section concludes this study and elicits its future policy implications.

Conclusion and Future Policy Implications

To conclude, the challenges and opportunities related to India's infrastructure and scalability for trade and logistics are crucial in determining its global role. As India strives to compete with China and become a global sourcing hub, the importance of strong logistics and shipping networks is paramount. The analysis of the LPI and the LSCI highlights both progress and areas needing improvement, when it comes to infrastructure and scalability. While there have been positive advancements, ongoing and strategic efforts are essential. Initiatives like the *PM Gati Shakti Yojana*, *NLP* and *Maritime India Vision 2030* demonstrate the GOI's resolve to address these challenges and promote sustainable development. India's tenacity to turn these challenges into opportunities reflects its ambition to not only compete but also lead in global trade and commerce. By capitalising on these opportunities, India can enhance its economic growth and establish itself as a significant player in the ever-evolving landscape of international trade logistics.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Kanupriya https://orcid.org/0000-0002-4186-4070

References

Atkinson, R. D., & Atkinson, R. D. (2024). *China is rapidly becoming a leading innovator in advanced industries*. Information Technology and Innovation Foundation.

Balu, B., Jayapal, R., Gunupuru, K. R., & Mogili, R. (2022). A conceptual roadmap for implementing localization in the Indian automotive industry in a post-pandemic scenario. *Academy of Strategic Management Journal*, *21*(S1), 1–15. https://www.researchgate.net/profile/Boopalan-Dr/publication/357736036_A_conceptual_roadmap_for_implementing_localization_in_the_indian_automotive_industry_in_a_post-pandemic_scenario/links/61dd30423a192d2c8af18e80/A-conceptual-roadmap-for-implementing-loc.implementing-localization-in-the-indian-automotive-industry-in-a-post-pandemic-scenario.pdf.

Brooks, S. G., & Wohlforth, W. C. (2015). The rise and fall of the great powers in the twenty-first century: China's rise and the fate of America's global position. *International Security*, *40*(3), 7–53.

Bukhari, S. R. H., Kokab, R. S., & Khan, E. (2024). The role of China in the global economy: Political strategies and economic outcomes. *Spry Contemporary Educational Practices*, *3*(1), 558–576.

Buye, R. (2021). Critical examination of the PESTEL analysis model. *Action Research for Development.* https://scholar.google.co.in/scholar?q=Buye,+R.+(2021).+Critical+examination+of+the+PESTEL+analysis+model.+Action+Research+for+Development&hl=en&as_sdt=0&as_vis=1&oi=scholart

CEIC. (2024). *Liner shipping connectivity index*. https://www.ceicdata.com/en/indicator/india/liner-shipping-connectivity-index.

Chandrasekhar, C. P., Ghosh, J., & Roychowdhury, A. (2006). The "demographic dividend" and young India's economic future. *Economic & Political Weekly*, *41*(49), 5055–5064. http://www.jstor.org/stable/4419004.

Christodoulou, A., & Cullinane, K. (2019). Identifying the main opportunities and challenges from the implementation of a port energy management system: A SWOT/PESTLE analysis. *Sustainability*, *11*(21), 6046.

Debourdeau, A., Schäfer, M., & Berlin, C. B. T. U. (2021). *Report on the PESTEL analysis of energy citizenship in Germany*. https://www.researchgate.net/profile/Ariane-Debourdeau-4/publication/370818446_Report_on_the_PESTEL_analysis_of_energy_citizenship_in_Germany/links/6464a66370202663165339b6/Report-on-the-PESTEL-analysis-of-energy-citizenship-in-Germany.pdf.

Deutch, J. (2018). Is innovation China's new great leap forward? *Issues in Science and Technology*, *34*(4), 37–47.

Dolgui, A., Ivanov, D., Sokolov, B., & Ivanova, M. (2017). Ripple effect in the supply chain: An analysis and recent literature. *International Journal of Production Research*, *56*(1–2), 414–430.

Foreign Policy. (2023). *Will India surpass China to become the next superpower?* https://foreignpolicy.com/2023/06/24/india-china-biden-modi-summit-great-power-competition-economic-growth/.

Global Data. (2024). *Labor cost index (LCI) of China*. https://www.globaldata.com/data-insights/macroeconomic/labor-cost-index-lci-of-china-2137631/

HSBC. (2024). *The next level: How Southeast Asia is moving up the value chain*. https://www.business.hsbc.com/en-gb/insights/growing-my-business/the-next-level-how-southeast-asia-is-moving-up-the-value-chain.

IBEF. (2024a). *About Indian economy: Growth rate & statistics*. https://www.ibef.org/economy/indian-economy-overview.

IBEF. (2024b). *India: A snapshot*. https://www.ibef.org/economy/indiasnapshot/about-india-at-a-glance.

India.Gov.in. (2024). *PM Gati Shakti national master plan*. https://www.india.gov.in/spotlight/pm-gati-shakti-national-master-plan-multi-modal-connectivity.

International Economic Association. (2024). *Projected labour force population of India and China*. https://www.iea-world.org/indias-population-surpasses-china-but-challenges-await-in-workforce-expansion-a-deep-dive/.

Invest India. (2022). *National logistics policy in India*. https://www.investindia.gov.in/team-india-blogs/national-logistics-policy-india.

ITC Trade Map. (2024). https://www.trademap.org/Index.aspx.

Jain, P., & Roy, A. (2024). Catalysts of innovation: Advancing India's future through investments in basic science. In *Unleashing the Power of Basic Science in Business* (pp. 91–117). IGI Global.

Jena, D. K. (2024). Beyond technology: Exploring sociocultural contours of artificial intelligence integration in India. *Educational Administration: Theory and Practice*, *30*(5), 1169–1184. https://doi.org/10.53555/kuey.v30i5.3031.

Kumar, V., & Singh, A. (2022). The 'National Logistics Policy 2022': An overview. *Indian Journal of Law & Legal Research*, *6*(4), 1.

Lazard. (2024). *The geopolitics of supply chains*. https://www.lazard.com/media/d4dnwbvc/the-geopolitics-of-supply-chains.pdf.

Madhani, P. (2008). Global hub: IT and ITES outsourcing. *SCMS Journal of Indian Management*, *5*(2), 108–114.

Manigandan, P., Alam, M. S., Murshed, M., Ozturk, I., Altuntas, S., & Alam, M. M. (2024). Promoting sustainable economic growth through natural resources management, green innovations, environmental policy deployment and financial development: Fresh evidence from India. *Resources Policy*, *90*, 104681.

Ministry of External Affairs, Government of India. (2021). *One of the youngest populations in the world—India's most valuable asset*. https://indbiz.gov.in/one-of-the-youngest-populations-in-the-world-indias-most-valuable-asset/.

Mishra, M. K. (2024). *Emergence of India as a key player in global economic affairs*. ResearchGate. https://doi.org/10.13140/RG.2.2.31037.06880.

Mitra, S. (2017). *Politics in India: Structure, process and policy*. Routledge.

Press Information Bureau (PIB). (2024). *Maritime India vision* 2030. https://pib.gov.in/PressReleasePage.aspx?PRID=2080012.

Quitzow, R. (2015). Assessing policy strategies for the promotion of environmental technologies: A review of India's National Solar Mission. *Research Policy*, *44*(1), 233–243.

Raman, H. (2016). *Dynamics of Indian economic growth: Can India become an economic powerhouse by 2025?* https://www.jru.edu.in/wp-content/uploads/RMJ/vol-11/Dynamics%20of%20Indian%20Economic%20Growth.pdf.

Rana, R. S., & Joshi, A. (2022). Exploration of Indian legal system from past to present. *Indian Journal of Law & Legal Research*, *6*(4), 1.

Shah, S. W. A., Afridi, S., & Madeeha, D. F. G. T. (2024). China's world order. *Remittances Review*, *9*(1), 2227–2239.

Singh, S., & Paliwal, M. (2015). India's demographic dividend: In the context of its economic growth. *World Affairs: The Journal of International Issues*, *19*(1), 146–157. https://www.jstor.org/stable/48505143.

Spoggi, G. (2020). Industry 4.0 and smart manufacturing: Potential environmental benefits. *The case of China*. http://dspace.unive.it/bitstream/handle/10579/18207/856705-1245335.pdf?sequence=2.

Srikrishna, B. N. (2008). The Indian legal system. *International Journal of Legal Information*, *36*(2), 242–244.

Economy.com., The Global (2024). *India: Political stability*. https://www.theglobaleconomy.com/India/wb_political_stability/.

UNCTAD. (2024). *Maritime transport indicators*. https://hbs.unctad.org/maritime-transport-indicators/.

Varghese, P. (2018). An India economic strategy to 2035: Navigating from potential to delivery. *The Australian Government.* https://www.dfat.gov.au/sites/default/files/minisite/static/07db88b0-d450-4887-9c90-31163d206162/ies/pdf/dfat-an-india-economic-strategy-to-2035.pdf.

World Bank. (2024a). *India at a glance*. https://www.worldbank.org/en/country/india/overview#1.

World Bank. (2024b). *Logistics performance indicators*. https://databank.worldbank.org/source/logistics-performance-index-(lpi).

Yang, D. T., Chen, V., & Monarch, R. (2010). *Rising wages: Has China lost its global labor advantage?* https://repec.iza.org/dp5008.pdf.

Zhang, B., Zhu, H., & Zhang, J. (2023). A portrait of China's economic transformation: From manufacturing to services. *China Economic Journal*, *16*(1), 14–27.

Zhao, C. (2023). Decoding China's thriving supply chain ecosystem. *FDI China*. https://fdichina.com/blog/supply-chains/

Review Essay

A Literature Review of Employee Moonlighting in the IT Industry and Its Impact

MDIM Journal of Management Review and Practice
3(1) 90–97, 2025

DOI: 10.1177/mjmrp.241297018
mbr.mjmrp.mdim.ac.in

Vishwa Rajesh Bhatt[1] and Pratha Jhala[2]

Abstract

The global economic landscape and environment are undergoing rapid transformations, prompting changes in human resource management (HRM) practices. The rise of flexible work arrangements, such as remote work and work-from-home options, offered primarily by IT companies, has led to a surge in moonlighting—where individuals take on secondary jobs to meet financial demands or to earn additional income. This shift reflects a growing concern among employees for financial stability rather than career growth amid economic uncertainties. Employees often work beyond their primary employment for extra compensation, impacting their work-life balance and employers' compliance policies. The phenomenon of moonlighting in the IT sector has become a point of concern, especially regarding its effects on efficiency. This study also looks at the prevalence of moonlighting in the IT industry and the connection between employees' primary and secondary jobs. Is it feasible for employees to work for multiple companies without their employer's knowledge? How can organizations provide financial support to reduce the appeal of moonlighting? What if employees could manage multiple roles efficiently without compromising any of them? Understanding when employees shift from occasional to full moonlighting is crucial for addressing these concerns.

Keywords

Moonlighting, part-time job, IT sector, side gig, freelancer

[1]Vidyabharti Trust College of Business, Computer-Science & Research (Affiliated to Veer Narmad South Gujarat University), Umrakh, Gujarat, India
[2]Department of Business and Industrial Management, Veer Narmad South Gujarat University, Surat, Gujarat, India

Corresponding author:
Vishwa Rajesh Bhatt, Vidyabharti Trust College of Business, Computer-Science & Research (Affiliated to Veer Narmad South Gujarat University), Umrakh, Gujarat 395007, India.
E-mail: bhattvishva01@gmail.com

Introduction

The flexibility within the IT industry has led to shorter job tenures and increased job instability. Consequently, individuals are seeking new ways to secure their income and maintain job stability. In today's labor market, job mobility has become vital due to the rapid pace of technological advancements and the constant need for skill upgrades (Ashwini et al., 2017). Many employees have adopted a flexible approach by taking on additional jobs or extending work hours to cope with this unpredictability. Multiple job holdings not only alleviate financial concerns but also ensure stable employment and opportunities for skill enhancement, contributing to career growth (Wisniewski & Kleine, 1984). As the IT industry becomes increasingly adaptable, moonlighting has emerged as a prevalent trend (George & George, 2022).

The relationship between employers and employees is crucial for an organization's success. Performance management motivates employees through incentives, training, and tangible and intangible rewards, fostering a high-quality work environment (Betts, 2006).In this complex network of organizations, moonlighting has become a significant challenge for both workers and businesses (Shaikh, n.d.; Special, 2022; Sussman, 1998). While some studies indicate that holding a second job can be exhausting, others suggest that, depending on the employer's practices and the work environment, it may provide opportunities for skill acquisition and knowledge development (Conway & Kimmel, 1992). Moonlighting has become a common practice in many labor markets, contributing positively to a country's economic development. Rapid changes in economic conditions, influenced by both micro and macroeconomic factors, have restricted job opportunities. As a result, moonlighting—or holding multiple jobs simultaneously—has become increasingly common in developed and developing nations. In Sri Lanka, for example, there is a lack of sufficient statistical data on the prevalence of multiple job holding compared to other countries (Labor Force Survey Annual Report, 2016).

Employee Moonlighting and IT Industry

The growing flexibility in the IT sector has shortened job durations, increased unemployment risks, and weakened employee–employer loyalty in recent times. Given these shifts, individuals are compelled to find alternative ways to maintain a stable income and secure employment. The rapid technological advancements and the continuous need for skills development have intensified the importance of occupational mobility in the modern labor market (Ashwini et al., 2017). Due to this uncertainty, a significant portion of the workforce has adopted moonlighting as a proactive coping strategy.

Working multiple jobs not only helps individuals manage financial challenges but also secures continuous employment and offers avenues for career progression by building specialized expertise (Hickey & Reist, 1979). Moonlighting has become more prevalent as the Indian IT industry has become increasingly adaptable. In this context, moonlighting refers to working a secondary job, often outside regular business hours, to supplement income. Some people moonlight out of necessity, such as when their primary job does not provide sufficient earnings, while others do so to gain additional income.

Taking up multiple jobs—whether full-time, part-time, or freelance—has become common in India. Due to stagnant wage growth, income levels have not kept up with the rising cost of living, leaving nearly one-third of people with side jobs struggling to meet their financial needs. Individuals often engage in side jobs to enhance their disposable income. When someone uses their primary job as a means to sustain themselves financially while pursuing a side career of their choice, this is commonly referred to as having a "day job" (Betts, 2002). Understanding the interplay between job mobility, moonlighting, and occupational experience is critical for shaping future IT industry policies and for gaining insights into income growth and career development (Kumaresh & Devi, 2020). Furthermore, taking on multiple jobs can negatively impact an employee's productivity, work-life balance, and health. As a result, organizations are developing innovative methods to motivate employees to perform more effectively. Companies must adapt to evolving work cultures and implement modern human resource practices to stay competitive in the global talent market.

Defining Multiple Job Holding

Extensive research has been conducted on people who work more than one job. In 1959, Bancroft first talked about this phenomenon. Numerous papers have since been published on the subject, despite the fact that it was not then generally acknowledged as an important field of study. Multiple job holding, dual job holding, second job holding, and moonlighting—the latter term being more prevalent in English-speaking nations—are some of the terms used in the literature to describe holding multiple jobs concurrently (Jamal & Crawford, 1981). Taking on a second part-time job at night to supplement inadequate income from one's primary employment is commonly referred to as "moonlighting" (Averett, 2001).

Research on managing multiple job holdings and their implications for human resource management (HRM) has not been found by the researcher. The impact of having multiple jobs on an employee's personal life and organization can impact HRM's role. Thus, the purpose of this study is to investigate how HRM may affect the results of holding multiple jobs. Second, the specific and distinctive Dutch public sector provided the unique setting in which this research was carried out. According to Dr. Brenda Vermeeren (2015), the United States and the United Kingdom have been the primary subjects of previous research. Financial stress is commonly cited as a reason for moonlighting, although modern lifestyles and nonfinancial motivations also influence the decision to take on additional work (Betts, 2002). This article discusses the effects of two nonfinancial motivations—job satisfaction and organizational commitment—alongside examining the mediating role of organizational commitment in the relationship between job satisfaction and intentions to moonlight (Seema, 2021).

Definition of Employee Moonlighting

Moonlighting refers to employees taking on additional part-time jobs or business activities simultaneously with their primary jobs to supplement their income (Gupta, 2009). Often, these side jobs are done discreetly, without informing the primary employer (*Economic Times India*).

Research on moonlighting identifies several types:

1. **Blue Moonlighting:** In response to demands for higher pay during performance evaluations, management may offer increased benefits. However, some employees may still find these benefits insufficient and may prefer to work part-time to earn more money. Without the requisite abilities, their endeavors might not be fruitful (Majumdar, 2022).
2. **Quarter Moonlighting:** An employee, after completing their education, may start in a lower-level management role. As time progresses and their family grows, they may find it difficult to manage their expenses with their current salary alone. To cope with these increasing financial demands, the employee begins to combine their primary job with a secondary one, which helps them meet their needs comfortably.
3. **Half Moonlighting:** Many individuals spend beyond their earnings. To balance this, they use half of their leisure time to earn additional money to save for the future or enjoy a luxurious lifestyle. This type of moonlighting is often observed among bank employees who monitor projects closely, ensuring loan repayments are made promptly, and they benefit from the successful outcomes of those projects.
4. **Full Moonlighting:** Individuals in certain professions who feel underpaid or have spare time may start their own businesses while maintaining their primary job. According to various studies, such dual-career paths influence their social and financial status. This situation, referred to as full moonlighting, involves managing two full-time jobs simultaneously (Bajpai & Nirwan, 2023; Tiwari, 2014).

Reasons for Engaging in Moonlighting

There are several reasons why moonlighting occurs. People frequently discover that their primary source of income is insufficient to cover their living expenses. The total income from one's primary employment may be impacted by laws governing working hours, short-term employment contracts, or the lack of minimum wage requirements (Preston, 2004). These difficulties may be made worse by financial difficulties that people or their families encounter, particularly for those who do not have time constraints at work but nevertheless fail to meet their income goals. Financial motivation is the term used to describe this situation.

Some workers may take on a second job in order to increase their options in the labor market and protect themselves from the possibility of losing their primary job. Instead of saving money when faced with challenging financial circumstances, some people choose to work two jobs (Gsuri & Thakkar, 2022). For example, IT professionals may look for a different job in order to gain skills that will help them transition into a new career. In these situations, moonlighting can be a means to learn new skills, improve employment prospects, or pursue entrepreneurial endeavors. The idea emphasizes the investment side of moonlighting over its consumption.

The theory of hours constraints suggests a negative relationship between an individual's intention to seek additional employment and the income they earn from their primary job. However, the variety of employment motives indicates that individuals may pursue part-time work for reasons unrelated to the hours worked or the pay (Kesavan, 2009). Early research on secondary job hours supports the hours-constraint theory, revealing that reductions in primary job hours and earnings are often associated with increased hours and income from secondary jobs (Dickey, 2011).

Employees who moonlight due to time constraints in their primary work may do so for shorter periods than those driven by intrinsic nonfinancial motivations. The traditional approach based on time constraints does not fully account for the fact that employees might eventually move past challenges in their primary job by seeking new opportunities. This casts doubt on the notion that moonlighting can solely be explained by time limitations. There is no definitive evidence suggesting that employees moonlight solely to counter job insecurity in their primary position (George & George, 2022).

Strategies and Policies to Manage Employee Moonlighting

People may secretly take on multiple jobs due to overtime requirements, layoffs, or moonlighting. These individuals might attempt to protect themselves by overcharging for their services; however, this may not align with the employer's interests (Rodell, 2013). High turnover rates caused by moonlighting have led to challenges for businesses, such as identifying and addressing the issue of dual employment. Companies often promote a trust-based and remote work environment, but it is crucial for entrepreneurs to recognize that maintaining moral standards and organizational order is challenging during turbulent periods (Conen & Stein, 2021).

Organizations must adapt their workplace culture to include policies that address moonlighting. For instance, companies can fill positions that employees genuinely want to pursue. Employers can also use software to monitor activities and prevent data breaches, thus reducing the risks associated with moonlighting (Misganu et al., 2022). Some organizations include clauses in their contracts that prohibit employees from taking on additional work without prior management approval. Employers should conduct frequent assessments to identify any red flags related to employee productivity and engagement, ensuring that all workers remain motivated (Employment Standard Act, 2000).

Current Moonlighting Situation in India

Moonlighting in India has garnered significant attention, with major companies weighing in on the issue (Mahankal et al., 2023). The debate centers on the ethics and legality of moonlighting. Some companies have already implemented policies to address the practice, including Wipro, TCS, and IBM, while others are considering similar actions (Jahangir & Tahseen, 2022). Many firms emphasize prohibiting employees from joining competitors or taking on roles that could create a conflict of interest (Rasdi et al., 2021).

Current Trends on Moonlighting Policies by Corporates

Companies Supporting Moonlighting:

- **Swiggy** has introduced a policy allowing its employees to take up side jobs under specific conditions.
- **Nova** promotes moonlighting, encouraging employees to explore new interests beyond regular work hours.
- **Tech Mahindra's** CEO has expressed openness to moonlighting, acknowledging its potential as the future of work.

Companies Against Moonlighting:

- **Wipro's** CEO labeled moonlighting as dishonest, leading to the termination of several employees.
- **IBM** and **TCS** have warned employees against taking additional jobs, citing ethical concerns and company culture. Infosys, however, has allowed side projects with prior approval.

Summary and Recommendations

Earning additional income from a secondary job can be crucial for individuals whose primary employment provides insufficient hours or income (Jain et al., 2023). The transfer of skills and knowledge between primary and secondary jobs creates a positive relationship between secondary employment and future career opportunities. Through secondary jobs, individuals can gain new competencies that may open up various career paths, including entrepreneurship (Seema & Sachdeva, 2019). When a person takes on a different type of work for their secondary job, they are more likely to transition to an entirely new career, leading to different employment opportunities in their next major job.

Secondary employment can lead to physical and mental strain, expose workers to unsafe or unregulated conditions, and reflect broader challenges faced by economically disadvantaged IT professionals who struggle to sustain an adequate standard of living with one job—especially in less developed countries (Mapira et al., 2023). However, when market failures necessitate action, policies must be carefully crafted to address the unique circumstances and motivations behind secondary employment. In general, policy intervention may not be necessary. For example, when secondary jobs are outside the IT sector (Gehlot & Bhati, 2023), governments should prioritize reducing unreported employment, protecting minimum wages, and enforcing health and safety regulations.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

References

Ashwini, A., Mirthula, G., & Preetha, S. (2017). Moonlighting intentions of middle level employees of selected IT companies. *International Journal of Pure and Applied Mathematics*, *114*(12), 213–223.

Averett, S. L. (2001). Moonlighting: Multiple motives and gender differences. *Applied Economics*, *33*(11), 1391–1410.

Bajpai, A., & Nirwan, N. (2023). A systematic literature review on moonlighting. *Global Journal of Enterprise Information System*, *15*(1), 102–109.

Betts, S. C. (2002). *An exploration of multiple jobholding (moonlighting) and an investigation into the relationship between multiple jobholding and work-related commitment*. Rutgers State University of New Jersey.

Betts, S. C. (2006). The decision to moonlight or quit: Incorporating multiple jobholding into a model of turnover. *Journal of Organizational Culture, Communications and Conflict*, *10*(1), 63.

Conen, W., & Stein, J. (2021). A panel study of the consequences of multiple jobholding: Enrichment and depletion effects. *Transfer: European Review of Labour and Research*, *27*(2), 219–236.

Conway, K. S., & Kimmel, J. (1992). *Moonlighting behavior: Theory and evidence* [Working Paper No. 92-09]. Upjohn Institute.

Dickey, H., Watson, V., & Zangelidis, A. (2011). Is it all about money? An examination of the motives behind moonlighting. *Applied Economics*, *43*(26), 3767–3774.

Employment Standards Act. (2000). *Government of Ontario*. Queen's Printer for Ontario. https://www.ontario.ca.

Gehlot, M. R., & Bhati, M. D. (2023). Evaluating technological disruptions in industrial processes. *Indian Journal of Business Innovation, 12*(1), 89–102.

George, A. S., & George, A. H. (2022). A review of moonlighting in the IT sector and its impact. *Partners Universal International Research Journal*, *1*(3), 64–73.

Gsuri, A. D., & Thakkar, M. D. (2022). Moonlighting: Emerging trends alter Covid-19 pandemic among employees. *Sankalpa*, *12*(2), 56–60.

Gupta, C. B. (2009). *Human resource management* (11th Thoroughly Revised Edition). Sultan Chand & Sons.

Hickey, J. L., & Reist, P. C. (1979). Adjusting occupational exposure limits for moonlighting, overtime, and environmental exposures. *American Industrial Hygiene Association Journal*, *40*(8), 727–733.

Jahangir, Y., & Tahseen, M. (2022). The impact of flexible work arrangements on job satisfaction. *Journal of Workplace Dynamics*, *33*(4), 251–267.
Jain, M., Gondane, H., & Balpande, L. (2023). Moonlighting: A new threat to IT industry. *International Journal of Information Technology & Computer Engineering*, *3*(4), 11–22.
Jamal, M., & Crawford, R. L. (1981). Consequences of extended work hours: A comparison of moonlighters, overtimers, and modal employees. *Human Resource Management*, *20*(3), 18–23.
Kesavan, B. S. (2009, December 1). Motivational factors in dual employment: A comparative study. *South Asian Journal of Management Studies, 17*(3), 301–319.
Kumaresh, S., & Devi, A. B. (2020). Exploring employee productivity and work constraints. *International Journal of Employment Studies, 45*(2), 105–123.
Mahankal, P., Shivane, A., & Singh, S. (2023). A review of moonlighting in the Indian it sector. *The Online Journal of Distance Education and e-Learning*, *11*(2), 1000–1007.
Majumdar, D. (2022). The employee moonlighting: A paradigm shift in socioeconomic context. *Globsyn Management Journal*, *16*(1/2), 63–69.
Mapira, N., Mitonga-Monga, J., & Ukpere, W. I. (2023). Moonlighting: A reality to improve the lived experiences of casual workers. *Expert Journal of Business and Management*, *11*(1), 48–59.
Misganu, G., Ayenew, Z., & Lemi, K. (2022). An integrative literature review: Tracing employee moonlighting as a thriving phenomenon. *Horn of African Journal of Business and Economics (HAJBE)*, *5*(2).
National Statistics Office. (2016). *Labor force survey annual report, 2016*. Government of Srilanka.
Preston, C. J. (2004). Moonlighting in these oppressive economic times. *University of Detroit Mercy Law Review*, *82*, 119.
Rasdi, R. M., Zaremohzzabieh, Z., & Ahrari, S. (2021). Financial insecurity during the COVID-19 pandemic: Spillover effects on burnout–disengagement relationships and performance of employees who moonlight. *Frontiers in Psychology*, *12*, 610138.
Rodell, J. B. (2013). Finding meaning through volunteering: Why do employees volunteer and what does it mean for their jobs? *Academy of Management Journal*, *56*(5), 1274–1294.
Seema, M., & Sachdeva, G. (2019). Moonlighting intentions of IT professionals: Impact of organizational commitment and entrepreneurial motivation. *Journal of Critical Reviews*, *7*, 214–220.
Seema, P. (2021). Impact of flexible working hours on job satisfaction. *Journal of Workplace Studies*, *10*(3), 200–215.
Shaikh, N. N. *A critical study on moonlighting the perception amongst the employers and its relevance in Indian context* [Doctoral dissertation].
Special, E. S. (2022 December 5). What is Moonlighting? What triggered the debate? And what is happening. *The Economic Times*. https://economictimes.indiatimes.com/news/new-updates/moonlighting-what-is-it-what-triggered-the-debate-and-what-is-happening/articleshow/94393239.cms
Sussman, D. (1998). Moonlighting: A growing way of life. *Perspectives on Labour and Income*, *10*(2), 24–31.
Vermeeren, B. (2015). Public management and employee outcomes: The role of managerial practices. *Human Resource Management Journal*, *25*(1), 45–59.
Wisniewski, R., & Kleine, P. (1984). Teacher moonlighting: An unstudied phenomenon. *The Phi Delta Kappan*, *65*(8), 553–555.

MDIM Journal of Management Review and Practice: Guidelines for Authors

Manuscript submission

- The preferred format for your manuscript is MS Word.
- The journal does not consider a paper that has been published elsewhere or that is under submission to another publisher. Authors must attest to this at the time of submission. It is also author's responsibility to disclose any potential conflict of interests regarding their submitted papers.
- Authors will be provided with a copyright form once the contribution is accepted for publication. The submission will be considered as final only after the filled-in and signed copyright form is received.

Basic formatting of the manuscripts

The journal publishes the following article types:

- Research Articles. The paper length should not exceed 8000 words including tables, references and appendices. Abstract (of up to 250 words) and 3-5 keywords are mandatory for an original research paper.
- Review Articles
- Case Reports
- Interviews

Please refer to the Submission Guidelines on the journal website for details on formatting.

Spelling and numerical usages

- Consistent use of either British or American spelling is advised, but not both at the same time.
- Spell out numbers from one to nine, 10 and above to remain in figures. However, for exact measurements use only figures (e.g. 3 km, 9%). Please use '13th' instead of 'thirteenth century'; use '1960s' instead of 'nineteen sixties'.

Quotations, notes, tables and figures

- British English uses single quotation marks to indicate quotations or dialogue, double quotation marks for quotation inside quotation (nested quotation). American English flips that method and uses double quotation marks to indicate quotations or dialogue, and single quotation marks for nested quotations.
- Notes should be numbered serially and presented at the end of the article. Notes must contain more than a mere reference.
- Tables and figures must be cited in the text, and indicated by number separately (Table 1), not by placement (see Table below). Source details for figures and tables should be mentioned irrespective of whether or not they require permissions.
- All photographs and scanned images should have a resolution of minimum 300 dpi and 1500 pixels, and their format should be TIFF or JPEG. Due permissions should be taken for copyright-protected photographs/images.

References and their text citations

- References and their citations should be given in accordance with APA 7th edition.
- Please ensure that all references mentioned in the reference list are cited in the text and vice versa.

For detailed style guidelines, please visit https://mjmrp.mdim.ac.in/