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Aims and Scope

IPE Journal of Management is a bi-annual, peer-reviewed journal which publishes empirical, theoretical and review articles dealing with the theory and practice of management. The aim of the journal is to provide a platform for researchers, academicians, practitioners and policy-makers from diverse domains of management to share innovative research achievements and practical experience, to stimulate scholarly debate both in India and abroad on contemporary issues and emerging trends of management science and decision-making.

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From the Editor's Desk...

The present issue for July-Dec 2023 presents a bouquet of seven articles from various domains. The first article of this issue is, “Unveiling Risk-Return Patterns in Actively Managed Equity Funds: An Analysis of the Indian Market”. The study emphases on a 10-year performance evaluation of 219 Indian equity growth funds over a period of a year. Based on eight matrices, this longitudinal performance analysis of actively managed funds explores patterns that can guide retail investors in making sound decisions. The second article is, “Financial Analysis of Domestic Systemically Important Banks (D-SIBs) in India: Bankometer and Zmijewski Models”. This article, examines the financial soundness of the three listed banks using the Bankometer and Zmijewski models for the period from 2014-15 to 2021-22. Both the models confirmed the three Indian banks as ‘supersound’ and ‘non-distressed’ during the period under review, thus establishing the correctness of assessment made by RBI. The next article is, “Impact of Regulation on Social and Financial Performance of MFIs: Evidence from India”. It examines if financial sustainability goals of Indian microfinance institutions (MFIs) conflict with the social objectives. The study also evaluates the impact of reforms directed mostly at regularizing financial performance of the MFIs, after a major crisis that destabilized the Indian microfinance sector in 2010. The article, “On-the-Spot Decision Making: A Bibliometric Investigation into Impulse Buying Research Progression, Network Structures and Emerging Trends” is a bibliometric study. It study are to synthesize existing literature on impulse buying, track its development over time, analyze intellectual and social structure based on this synthesis, and propose cluster-based themes for future research in the domain of impulse buying. The next article, “TFP Growth in Manufacturing Sector: Evidence from India and China” uses growth decomposition method to estimate the contribution from input growth, scale effect, technical progress and technical efficiency towards output growth between India and China. The next article is, “Impact of Workplace Ostracism, Emotion Exhaustion on Employee Engagement and Employee Wellbeing Among it Women Professionals in India”. It discusses, the effects of workplace ostracism, emotion exhaustion on employee engagement and employee wellbeing among IT women professionals working in IT companies located in various states in Southern India. The final article is, “Capturing Netizens’ Sentiment of Electric Cars through Twitter Using NVivo”. This study ascertains how people generally feel about the category of electric cars, the current study using sentiment analysis.

I look forward to focusing on issues that cultivate new management thinking. I expect authors would channel their expertise to focus on challenges faced by corporates, public sector units and society. In the coming times, IPE journal of management would encourage articles featuring innovative, technically sound and original research that contributes to management theory.

Samarendra Kumar Mohanty

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Unveiling Risk-Return Patterns in Actively Managed Equity Funds: An Analysis of the Indian Market

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Abstract

The volume and participation of the Indian mutual fund business have grown substantially in the last decade. This surge in activity has prompted researchers to step in and undertake a comprehensive evaluation of the fund managers' aptitude to manage such vast pool of corpus due to the skyrocketing number of portfolios and enormous AUM. The study emphases on a 10-year performance evaluation of 219 Indian equity growth funds over a period of a year. Based on eight matrices, this longitudinal performance analysis of actively managed funds explores for patterns that can guide retail investors in making sound decisions. The results demonstrate that Indian fund managers perform slowly; they were unable to provide investors the desired return since active funds generally failed to disclose excess return relative to the specified benchmarks. The managers of the funds adapt to market developments. The investigation determined that they are highly natural at handling losses and reducing risks. The risk management strategies are based on the stock specific fund management and dispersion from benchmarks during the downturn of the market. The current study contributes to the knowledge of the rational investors who can make informed decision making.

Keywords: Benchmark Comparison, Mutual Funds, Performance Evaluation, Risk and Return

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Introduction

The investment landscape in India has witnessed a transformative journey, particularly in the realm of mutual funds. The Indian Mutual Fund (MF) industry stands as a testament to its remarkable growth story, a narrative woven with burgeoning Average Assets Under Management (AAUM) and expansive Assets Under Management (AUM). In April 2023, the AAUM reached an impressive ₹41,52,715 Crore, underscoring the industry's prominence as a favoured investment avenue. Additionally, the AUM of the Indian MF industry as of April 30, 2023, soared to ₹41,61,822 Crore, a testament to the sector's resilience and financial prowess.

This journey of expansion is marked by significant milestones, reaffirming the industry's significance. In May 2014, the sector reached a pivotal moment by surpassing the ₹10 trillion (₹10 Lakh Crore) AUM threshold. Swiftly, within three years, an outstanding two-fold increase was achieved, crossing the ₹20 trillion (₹20 Lakh Crore) mark in August 2017. The upward trend persisted, reaching its peak when the AUM surpassed ₹30 trillion (₹30 Lakh Crore) in November 2020. As of April 2023, the Industry AUM stands at ₹41.62 trillion (₹41.62 Lakh Crore), reinforcing the sector's robust growth and financial prominence.

The industry's importance is underscored by reaching another significant achievement - 100 million folios in May 2021. The total number of accounts, or folios, surpassed 146.4 million by April 2023. Particularly, folios in Equity, Hybrid, and specific objective-oriented schemes, serving the retail sector, made up approximately 116.9 million, demonstrating the industry's appeal to retail investors. This surge in interest has been further fuelled by endorsements from prominent figures, government officials, and favourable developments that have uplifted the Mutual Fund industry.

Despite being investment experts, mutual fund managers are human and are susceptible to error. It might be difficult for mutual fund managers to consistently outperform the market or their benchmark indices. This may be the result of factors like poor stock selection, poor risk management, or a lack of capacity to adjust to shifting market conditions. The herd mentality, when fund managers follow the investing choices of their peers rather than undertaking their own independent research and analysis, may prevail. The profits on the fund may be eroded by frequent buying and selling of securities, which can result in high transaction costs. Ineffective risk management by fund managers could result in substantial losses during market downturns. Mutual fund managers, just like any other investor, are susceptible to cognitive biases such as Self-attribution, loss aversion, and overconfidence bias. These biases can impact their decision-making process and lead to unfavourable investment choices. However, it is crucial to highlight that not all mutual fund managers possess these flaws. In reality, many of them are competent individuals who consistently strive for successful outcomes. Therefore, investors should conduct comprehensive research and remain cognizant of these potential risks when choosing a mutual fund.

In light of this evolving investment landscape and under error-prone mindset of fund managers, it becomes essential to conduct an extensive analysis of performance of the mutual fund managers in this dynamic market. The main goal of this investigation is to make a valuable contribution by exhaustive analysis of the efficacy of fund managers within Indian ecosystem. Furthermore, this analysis holds substantial importance as it strives to provide investors with invaluable guidance, enabling them to make informed choices regarding their investment alternatives. Furthermore, current research on the Indian mutual fund business frequently takes a cross-sectional approach, leaving great room for investigation into the long-term performance of fund managers.

Therefore, by conducting a comprehensive, ten-year analysis of the outcomes of professionally managed equity growth funds in India, this research serves as a bridge to close this gap. This investigation is underpinned by an extensive array of risk and return analyses, aimed at uncovering whether the achievements of fund managers can be attributed to true managerial prowess or whether they simply mirror the trends dictated by the market.

This paper goes beyond mere historical performance; it examines the investment choices made by fund managers, gauging their alignment with prevailing market patterns. The aim is to determine whether these managers consistently outperform the market while exercising sound judgment under diverse market conditions. This study is especially significant due to how it may foster investors with the information they require to comprehend the complex aspects of investing in mutual funds.

As the Indian mutual fund industry continues on its trajectory of unparalleled growth, deciphering the complexities of fund manager performance becomes a pressing endeavour. This paper embarks on this journey, contributing to the expanding corpus of knowledge concerning mutual fund performance evaluation. Through insights into fund manager behaviour and performance, this research equips investors with the tools they need to make astute investment choices, thereby furthering the growth trajectory of the Indian mutual fund industry.

The subsequent part of this paper will focus on the vast body of literature pertaining to the subject. Following that, the third segment will provide a comprehensive overview of the methodology employed to assess the risk and return associated with mutual funds. Moving on to the fourth section, the research will showcase its discoveries and delve into the implications. Lastly, the study will aim to draw conclusions in the final section.

Literature Review

Popular metrics used for assessing the mutual fund performance include the Jensen's Alpha(*1968*), Treynor index *(1965)* and Sharpe index(*1966*). These metrics, along with regression analysis, stochastic dominance analysis, bootstrap approaches, and information ratios (IR), aim to assess performance persistence and predictability. They also consider the relationship between excess returns and risk exposure. Nevertheless, it is important to acknowledge that a broader set of factors can lead to contradictory outcomes and varying fund rankings. For example, factors such as market conditions, economic cycles, fund manager skill, investment strategy, and fund size can all impact the performance of a mutual fund *(Low, 2012; Mansor, Bhatti, & Ariff, 2015)*.Furthermore, there is no standard approach for evaluating the efficacy of mutual fund portfolios.

The impact of the business cycle or the effects of the economic cycle may be the reason why the performance evaluation of mutual funds received mixed reviews throughout the time. Studies have shown a straightforward buy-and-hold approach performs better than fund managers with skill *(Menkhoff & Schmidt, 2005)* due to the fact that the economic cost of this strategy is relatively lower *(O'Brien, 2020)*. The ability to time the market is a crucial ability for fund managers, but in US markets, managers continue to lack competence *(Treynor J. L., 1965)*. Nevertheless, managers are outperforming benchmarks and producing abnormal returns thanks to the capacity to predict security prices *(Wang C., 2011)* rather than the ability to time the market *(Koutsokostas, Papathanasiou, & Eriotis, 2018)*. There is some evidence that certain fund managers can pick securities with excessively good returns *(Pinnuck, 2003; Avramov & Wermers, 2006)* which are then offset by high expenses and load charges *(Sharpe W. F., 2013)*. There exist economies of scale between expense ratio and size of funds *(Filip & Karaś, 2019)*.

Recent developments show persistence in the selection of securities and market timing, which are statistically and economically significant but can be detected for short interval*(Riley, 2021)* and mainly from the loser funds (*Deb* S. G., 2019) when the performance of these funds is assessed numerous times throughout a single year *(Bollen & Busse, 2005; 2001)*. Furthermore, researchers concluded that judgments about market exposure are frequently made over shorter time horizons, like daily for various funds, therefore the monthly data might not adequately reflect the capacity to time the market *(Goetzmann, Ingersoll, & Ivković, 2000; Bollen & Busse, 2001)*. Researchers, *(Leite & Cortez, 2009; Tan, 2015; Deb, Banerjee, & Chakrabarti, 2007)* however, had been unable to stumble upon any proof of fund managers' capacity to choose effectively and time the market.

Researchers employ a variety of methodologies for evaluating risk-adjusted performance, and due to the measurement approach, Sharpe and

Treynor can produce results that are comparable *(Almonte, 2013)*. Market dynamics, size of the sample, and duration of investment may all influence the extent to which a performance is evaluated. Alternative performance evaluation techniques viz., Sortino ratio *(Sortino & Price., 1994)*, the Information ratio *(Treynor & Black, 1973)*& appraisal ratio that reflects stock selection abilities of funds *(Wang Y. A., 2017)*may enhanced the funds' performance assessment..

On a specific note, Kiymaz *(2015)*investigates the effectiveness of Chinese mutual funds by analyzing various performance indicators such as the Sharpe index, Information ratio, Treynor index, M-squared, and Jensen's risk performance indicators. The results of the study suggest that Chinese mutual funds provide their clients with favourable returns because the alpha is positive. Nevertheless, the study ultimately determines that Chinese funds do not consistently generate additional returns. The efficacy of Pakistani closed-ended mutual funds was investigated by Bilawal et al. *(2016)*using a variety of metrics, including Treynor, Jensen alpha, Sharpe, Sortino, and information ratios. The report reveals that whereas other measures show significant underperformance, the Treynor and Information measurements reveal satisfactory performance.

Tripathi and Japee*(2020)*conducted a study where they found that a significant majority, specifically two thirds, of the sample funds in the Indian mutual fund industry outperformed the index. Consequently, they recommended the utilization of risk adjusted performance evaluation methodologies. According to Venugopal and Sophia *(2020)*, Sharpe was the best assessor during the COVID-19 financial crisis that hit the Indian mutual fund market. Agarwal and Mirza observed that the Sharpe and Treynor indices outperformed the benchmark 90% of the time*(2017)*. However, they also observed that negative performing funds are more consistent than the others.

On the other hand, Ali and Qudous(2012) use the Sharpe and Treynor model to assess the efficacy of MFs with a sample size of 15. The analysis concludes that the sample MFs' performance is subpar when compared to the return of the benchmark portfolio. Nafees and Shah (2011) use the Sharpe, Treynor, Sortino, Jensen differential model and information measure to evaluate the performance and according to the analysis, certain funds surpass benchmark returns while others show underperformance returns. Ritesh(2016) examined 3 years longitudinal data and concluded none of the performance evaluator do not work well in Indian markets.

The prevailing research has revealed varying levels of documentation regarding the outperformance and underperformance of funds over time (Rao, Tauni, Ahsan, & Umar, 2020). The bulk of studies in the mutual fund industry have primarily been cross-sectional in nature. This study aims to address this gap by embarking on a longitudinal study spanning a decade, focusing on actively managed equity growth funds. The researcher's analysis only took into consideration a fund's performance over a one-year period due to the transient and inconsistent nature of a manager's stock selection abilities.

Research on the long-term assessment of professionally managed equity growth funds' performance in India is lacking. The current study examines a variety of financial metrics over a ten-year period in an effort to ascertain whether fund managers in India exhibit true managerial competence or if their performance is solely the outcome of adhering to normal market trends. These findings can be used by investors to make informed investing decisions. This article offers a thorough examination of the efficacy of mutual funds in the country with the goal of offering investors insights into benefits as well as challenges experienced by fund managers during the investment journey. The research aims to investigate the behavioural tendencies exhibited by fund managers at various phases of market movements, enabling investors to anticipate comparable responses from these fund managers in subsequent situations. Furthermore, by examining both short- and long-term performance trends, the investigation will contribute to the corpus of existing research on mutual fund performance evaluation.

Methodology

A well-informed investment decision requires lots of self-research and market knowledge that normal investors may lack, due to over information. The study is carefully examining the mutual fund performance using a sophisticated methodology that includes a wide variety of financial parameters. Additionally, it carefully evaluates the risks associated to funds. The goal of the study analysing the fund performances using various risk and return parameters.

Data Collection and Data Sanitization

The researchers initially gathered a thorough list of 12473 mutual funds from the AMFI website[1], which was then filtered for scheme codes only for the "Direct Funds" that were included in the list. Since equities mutual funds are the most active funds in the Indian capital market, only these funds were used in the study. The study exclusively focused on "growth" funds due to its emphasis on analyzing the continuous and long-term performance of these funds.

The researchers source the historical data of all direct equity mutual funds for growth category using Python and the MFTOOL and PANDAS tools. These equity mutual funds have been categorized by AMFI into eleven sub-categories viz. thematic, contra, dividend yield, ELSS (Equity

1 https://www.amfiindia.com/

Linked Savings Scheme), flexi cap, focused, large cap, large-mid cap, mid cap, small cap, and value funds.

To reduce the Total Expense Ratio (TER), all Asset Management Companies (AMCs) are required by SEBI guidelines[2] to implement direct investment funds. All currently operating AMCs implemented the NAV for direct plans as of January 1st, 2013. As a result, researchers chose 2013 as the evaluation's starting date. According to Deb(2019), it is important to consider at least 5 years of data when assessing the performance of mutual funds.

Table-1: Total Number of Funds in Study

Sl. No.	Types of Funds	No. of Funds as on 31st Dec 2022	Funds Launched Prior to 2018
1	Large Cap	28	22
2	Thematic	112	56
3	Value Fund	19	11
4	Multi Cap	13	6
5	Small Cap	23	13
6	Dividend Yield	8	4
7	Contra	3	3
8	Large Mid Cap	26	20
9	Mid Cap	25	19
10	Focused	25	14
11	Flexi Cap	30	21
12	ELSS	38	30
		350	219

Considering that, only those funds are considered which have at least five years' worth of historical data. The literature supports the method and emphasizes the significance of taking into account a rational time period to accurately evaluate the capabilities of fund managers. By utilizing this timeframe (2013-2022), the study is able to document performance trends in both the short-term and long-term, extending up to the current date.

As observed in the previous sections, that the skills of fund managers tend to be short-lived, therefore, to accurately assess their abilities and account for the impact of market fluctuations over time, the researchers decided to evaluate funds' performance on a yearly basis i.e., performance evaluation for last one year was done and compared those performances over the ten-year period. This approach allows us to uncover any patterns of consistent outperformance or underperformance, and it enables us to identify managerial insight amidst changing market conditions and economic cycles.

2 https://www.sebi.gov.in/legal/circulars/sep-2012/steps-to-re-energise-mutual-fund-industry_23440.html

Variables and Methods

A wide range of financial measures have been taken into account in order to provide an overall review. These indicators include mean return, cumulative returns, excess daily return over benchmark, and annualized risk premium, which measure a portfolio's capacity for outperformance and producing excess returns. Mean return and cumulative returns provide a fundamental grasp of overall performance. Risk is measured by daily and annual volatility, while tracking error and mean difference over benchmark evaluate consistency of fund's performance in comparison to the benchmark. While semi-variance concentrates on downside risk, cumulative excess return over benchmark indicates overall outperformance. Portfolio beta over benchmark and idiosyncratic risk assesses the susceptibility to market changes and diversifiable risk elements, respectively. The researchers' thorough examination of these factors provided insight into the fund managers' decision-making process, risk management abilities, and overall performance vis-à-vis market trends.

The study employed single index regression model (Sharpe W. F., 1963), to evaluate the Jensen's alpha, Beta and idiosyncratic risk (standard deviation of the residuals). To enhance the evaluation process, multiple benchmarks, as mentioned in the AMFI website, are employed as reference points for comparison. These benchmark comparisons serve as crucial yardsticks in discerning the impact of managerial decisions and strategy execution.

By adopting this rigorous and multi-faceted approach, the research aims to make robust conclusions about the presence of genuine managerial skill in the fund's performance, contributing valuable knowledge to the realm of investment analysis and portfolio management.

Performance Metrics and Evaluation Criteria

The performance of the selected funds was evaluated using various financial metrics. These metrics include mean return, cumulative return, excess daily return over benchmark, annualized risk premium, daily and annual volatility, and tracking error.

a. **Mean Return:** The mean return is the average daily return of the fund over the analysis period. By expressing metrics like the mean return on an annualized basis, the study ensures consistency and coherence in evaluating the fund's performance, enabling more informed and insightful decision-making for investors and portfolio managers. The formula for mean return is:

$$\overline{r_i} = \frac{1}{n_t} \sum_{t=1}^{n_t} r_t \qquad \text{... (1)}$$

Where:

r_t = the daily returns

$\bar{r}_i$ = Average return of the fund i

n_t = the number of days for particular year

The mean return provides an indication of the fund's average performance over the analysis period.

b. **Cumulative Return:** The overall return of the funds during the analysis period is known as the cumulative return. The formula for cumulative return is:

$$r_a = \left[\prod_{t=1}^{T}[1 + r_t]\right] - 1 \qquad \text{...(2)}$$

Cumulative return (r_a) calculates a mutual fund's overall percentage gain or loss over a specified time period (T). This is a vital instrument for comprehending how compounding affects the growth of investments. It takes into account the compounding impact, which may significantly boost returns over time, in addition to the fund's performance in absolute terms.

c. **Cumulative excess Return over Benchmark ($CERB_t$):** This measure of return performance reveals whether a fund has outperformed or underperformed a given benchmark by comparing its daily return to that of the benchmark. The formula for excess daily return over the benchmark is:

$$CERB_t = \frac{(r_{i,a} - rb_{i,a})}{|rb_{i,a}|} \qquad \text{...(3)}$$

Where:

$rb_{i,a}$ = cumulative returns of the benchmark

In the event that the fund's cumulative excess return surpasses the benchmark, it has outperformed the benchmark; if not, it has underperformed.

d. **Annualized Risk Premium:** The difference between the yearly return of the fund and the risk-free rate is known as the annualized risk premium, and it denotes the additional return that comes with taking on greater risk. The formula for annualized risk premium is:

$$AnnualizedRiskPremium = Avg\,(r_{i,t} - r_f) \times n_t \qquad \text{...(4)}$$

Where:

r_f = daily risk-free rate.

$n_t = Number of days in a year$

The annualized risk premium is a measure of the higher return a fund generates for accepting greater risk. An investment fund that exhibits a positive annualized risk premium delivers returns that exceeded the r_f, perhaps signifying prudent risk-taking and efficient risk management. Conversely, an adverse premium suggests that the fund stumbled relative to the risk-free investment, which can prompt investors to reconsider the fund's risk profile and management style.

Risk Analysis

A variety of factors, including tracking error, semi-variance, portfolio beta over benchmark, and idiosyncratic risk, can be used to assess the risk of the fund.

a. **Tracking Error:** The tracking error, which measures the consistency of a fund's performance against its benchmark, is computed using the standard deviation of the variation between the fund's returns and those of its benchmark. The formula for tracking error is:

$$\sigma_{i,t,\varepsilon} = \sigma(r_{i,t} - rb_{i,t}) \times \sqrt{n_t} \qquad \text{...(5)}$$

Where:

$\sigma_{i,t,\varepsilon}$ = Tracking error

σ = standard deviation

$rb_{i,t}$ = daily benchmark return

$n_t = Number of days in a year$

A measure of the consistency in the fund's return in contrast to the benchmarks is the tracking error. An investing strategy and benchmark selection that are strictly adhered by the fund is indicated by a low tracking error, which implies that the fund closely tracks the benchmark. Conversely, a greater tracking error could indicate active management choices or departures from the benchmark, which could provide investors advantages as well as disadvantages.

Semi-Variance: With certain asset classes like stocks, MF, currency & Commodities or portfolio strategies (options like features) the return distribution is asymmetric (with fat-tails). Semi-variance *(Markowitz, 1959)* is computed by squaring only negative deviations from the mean. It is determined as the average of the squared deviation of returns below the average return and serves as an indicator of downside risk. The formula for semi-variance is:

$$\overline{\overline{\sigma^2}} = E[\min\,[r_{i,t} - \bar{r}, 0]]^2 \text{If}\left(r_{i,t} < \bar{r}\right), \, then\left(r_{i,t} - \bar{r}\right); \text{If}\left(r_{i,t} > \bar{r}\right), \, then\ 0$$

$$\overline{\overline{\sigma^2}} = \frac{1}{n_t}\sum_{t=1}^{T} \min\,[r_{i,t} - \bar{r}, 0]^2 \qquad ...(6)$$

Where: $\overline{\overline{\sigma^2}}$ = Semi-Variance

Semi-variance provides an indication of the volatility in the fund's returns below the mean returns. It is a useful metric for investors who are more concerned with downside risk than upside potential.

b. **Portfolio Beta over Benchmark:** Portfolio beta over benchmark is the sensitivity of the fund's returns to the benchmark returns, indicating the fund's systematic risk. The formula for portfolio beta over benchmark is:

$$r_{i,t} - r_f = \alpha_{i,t} + \beta_{i,t} \times \left(rb_{i,t} - r_f\right) + \epsilon_{i,t} \qquad ...(7)$$

Where:

$r_{i,t} - r_f = excess\ return\ on\ asset$

$rb_{i,t} - r_f = excess\ return\ on\ bench\ mark$

$r_f = risk\ free\ return$

The portfolio's beta relative to the benchmark indicates how susceptible the fund is to systematic risk. When the beta of a fund is 1, it means that its returns follow the benchmark's movement; when the beta is higher than 1, it means that the fund's returns move differently from the benchmark.

c. **Idiosyncratic Risk:** After taking systematic risk into consideration, idiosyncratic risk refers to the fund's unsystematic risk, which is determined using a single index model. Idiosyncratic risk has an impact on fund performance, which can affect the fund's capacity to produce returns above alpha. A knowledgeable fund manager, who will produce greater risk-adjusted returns managing the risk by diversification of combining assets from different investors, which lowers exposure to specific securities and industries. Idiosyncratic risk, which highlights particular risks associated to certain assets in the fund, can have an impact on stock selection, can be reduced with the aid of proper risk management approaches, which can minimize volatility and stabilize returns. Idiosyncratic risk provides an indication of the fund's exposure to unsystematic risk. The formula for idiosyncratic risk is:

$$RSE_t = \sqrt{\frac{\sum_{j=1}^{n} \epsilon_j^2}{n_t - k}} \quad ...(8)$$

$$\sigma_{i,t}^{\epsilon} = 100 \times RSE_t \times \sqrt{n_t} \quad ...(9)$$

Where:

The residual standard error RSE_t from regression is calculated using eq.7. Where n_t is the number of days in a year and k is the number of parameters estimated by the regression.

$\sigma_{i,t}^{\epsilon}$ = Idiosyncratic Risk of the fund 'i' for the year 't'.

These measures are essential tools in the field of performance evaluation and investment analysis, providing quantitative measures to evaluate the effectiveness of various investment vehicles and strategies.

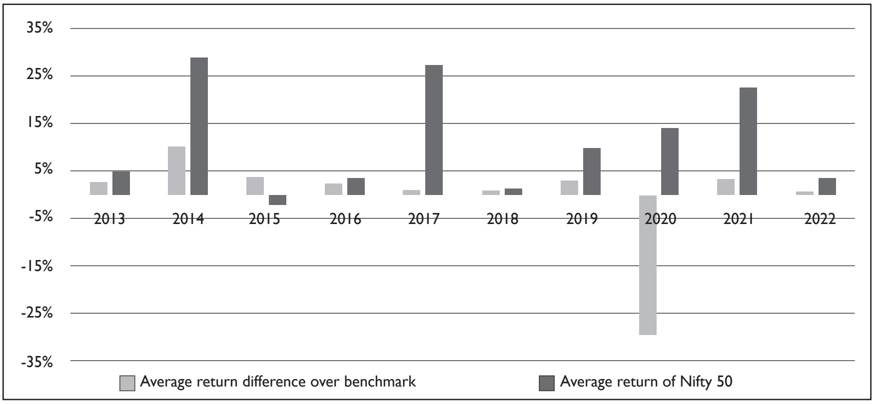
Analysis & Interpretation

The investigation has been separated into two primary parts: return assessment and risk assessment in order to guarantee a thorough understanding. The return analysis includes the examination of the average return difference over benchmark (ARDB), which demonstrates how the funds have either outperformed or underperformed their respective benchmarks. This difference in returns is quite significant in absolute terms. As a result, in order to better understand what happens to the excess return above the risk-free return earned in comparison to the benchmarks, researchers additionally looked into the Cumulative Excess Return Over Benchmark (CERB). This parameter provides valuable insights into the fund's performance. Additionally, in order to comprehend the risky assets of mutual funds and evaluate the fund's performance, the researchers analysed the Annualized Risk Premium (ARP). The returns of Nifty 50 are used as a benchmark for comparing all three parameters. Despite the difference in base, the researchers conducted a unique study to analyse how market performance impacts these parameters, even though they are not directly comparable to Nifty 50.

ARDB Analysis

The data presented in *Figure-1* indicates that, apart from a single occurrence, the Nifty 50 exhibited significantly better performance compared to the mutual funds under scrutiny. With the exclusion of the year affected by the pandemic, the average fund performance fell short of exceeding 5% in nine out of ten instances. It was only in 2015 that ARDB managed to outperform the market amidst a downturn. Similarly, during years of poor market performance such as 2016 and 2018, ARDB also showed stagnant results.

Figure-1: Comparative Analysis of ARDB with Returns of Nifty 50



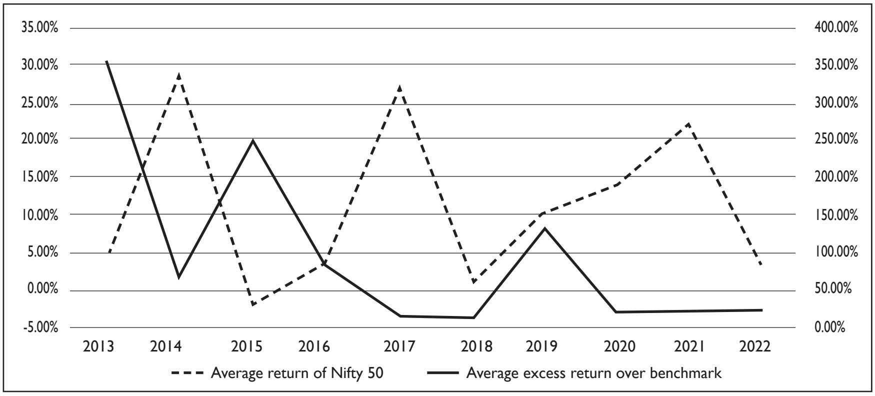
CERB Analysis

The persistent excess return data offers insightful information about the fund manager's capabilities to deliver gains that are higher than average. Over the last decade, this data strongly suggests a continuous downward trend (*Figure-2*), indicating that the fund manager's performance has been deteriorating over time. This trend is evident of a consistent decline in excess returns. This declining trend suggests that the active fund manager appears to be having difficulty providing investors better returns.

Though, it is significant to note that there have been some notable exceptions to this downward trend. In 2013, 2015, and 2019, significant cumulative returns were observed, indicating that the fund manager was able to generate substantial profits during these periods. Despite of the fact that in these years likely Nifty 50 returns are not very impressive. On the other hand, despite robust economic growth in years like 2014, the average cumulative returns in 2017 and 2021 remain relatively low. This suggests that the fund manager's performance has been lacklustre during these years, as they have failed to capitalize on the favourable market conditions and generate significant returns for investors.

This sluggish response from the fund manager in 2017 and 2021 indicates a failure to anticipate and react to significant market shifts. Instead of proactively adjusting their investment strategy to take advantage of emerging opportunities, the fund manager seems to have opted for a slow reaction in alignment with prevailing market trends. This reactive approach may have resulted in missed opportunities and subpar performance.

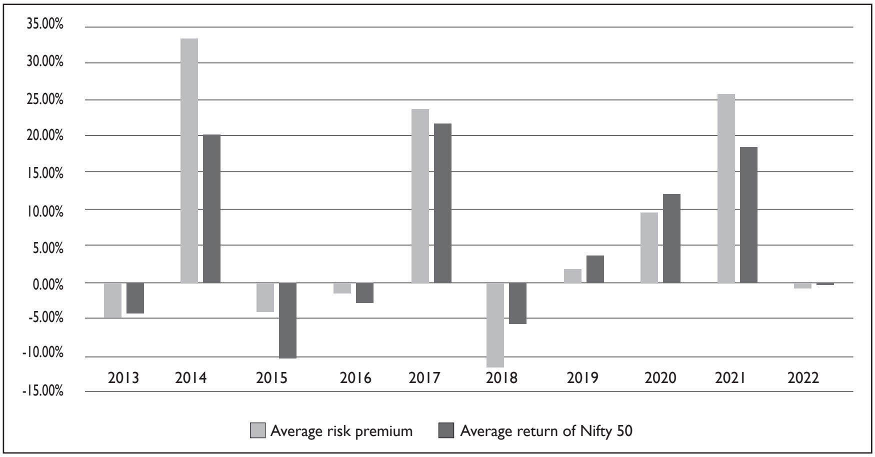
Figure-2: Comparative Analysis Between CERB and Nifty 50 Returns



Risk Premium Analysis

Risk premium has a significant positive correlation with the risk-adjusted returns of the Nifty 50 when assessed. There are three notable years with improved results – 2014, 2017 and 2021 – where fund risk premiums beat key market returns (*Figure 3*).

Figure-3: Comparative Analysis Between Fund's Risk Premium and Risk Adjusted Nifty 50 Returns



Risk Analysis

The researchers conducted a comprehensive analysis of risk in order to provide an accurate assessment of the expected risk faced by fund managers over the past ten years. They utilized five key metrics to evaluate risk, including excess volatility over the benchmark, semi variance, tracking error, beta over the benchmark, and idiosyncratic risk. By considering these metrics, the researchers were able to gain a holistic understanding of the risk profile of fund managers. The mean values of all the selected parameters are presented in (*Table-2*). The skill of fund managers in mitigating excess volatility within their portfolios is evidently demonstrated. *Table-2* reveals negative values for each year in which fund managers maintained low volatility than the benchmark risk. Furthermore, the analysis revealed that fund managers exhibited considerable adeptness in safeguarding capital during the COVID-19 years. This suggests that fund managers were able to effectively navigate the unprecedented market volatility and protect the value of their funds. This finding highlights the importance of proactive risk management strategies employed by fund managers, as they were able to successfully mitigate the adverse effects of market downturns. It is primarily evident that the primary objective of fund managers is to proactively avert excessive volatility and preserve the value of the fund.

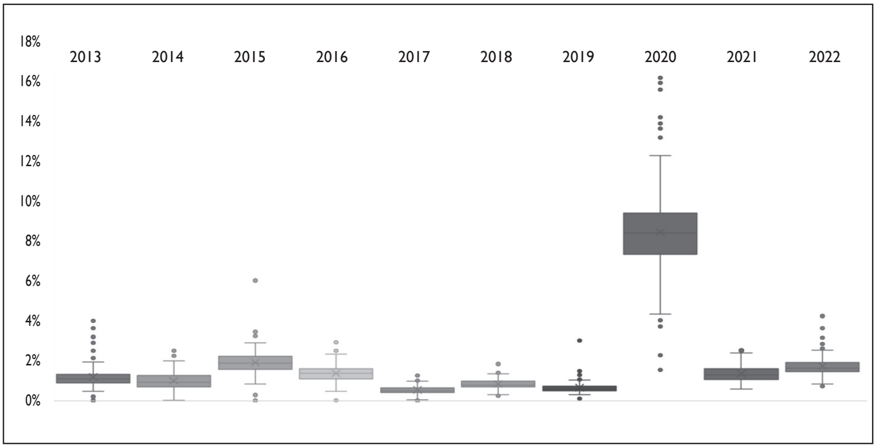
Table-2: Averages of Risk Parameters

Averages of Particulars	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Excess Vol. over Benchmark	-1.72%	-1.19%	-3.39%	-1.01%	-0.39%	-1.19%	-3.18%	-57.34%	-1.83%	-0.67%
Semi Variance	1.81%	1.51%	2.46%	1.86%	1.03%	1.21%	2.21%	8.37%	1.78%	2.10%
Tracking Error	8.55%	9.0%	12.93%	8.05%	6.5%	7.55%	11.65%	72.63%	7.09%	7.84%
Portfolio Beta over Benchmark	0.7418	0.7157	0.6492	0.8113	0.7729	0.7719	0.6348	0.5830	0.8339	0.8333
Idiosyncratic Risk	6.73%	9.54%	9.61%	7.67%	6.16%	6.80%	8.38%	16.85%	7.02%	7.64%

The same idea was supported by the average semi variance. The emphasis on mitigating downside risk is a key strategy employed by Indian fund managers to protect their investments and ensure stable returns for their clients. By consistently keeping the average semi variance within the 1% to 2% range, fund managers demonstrate their commitment to preserving capital and minimizing losses during periods of market volatility. The significant increase in average semi variance in 2020, driven by the unprecedented challenges posed by the COVID-19 pandemic, highlights the importance of risk management in the investment process. Despite this outlier, Indian fund managers have shown resilience in navigating turbulent market conditions and maintaining a disciplined approach to managing downside risk. The data presented in *Table-2* and *Figure-4* underscore the prudent risk management practices adopted by Indian fund managers, which have enabled them to effectively navigate market uncertainties and deliver consistent returns for their investors.

In comparison to the selected benchmark, Indian fund managers demonstrate superior investment decision-making skills, as evidenced by their tracking errors. According to *Table-2*, active Indian fund managers frequently make decisions that result in a significant deviation from the benchmark, during 2013-2016 ranging from 7% to 12%.Higher tracking error could suggest active management strategies. During 2017-2019, there is a downward trend in tracking errors. After a spike in 2020, tracking error stabilised in single digit in 2021-2022. However, the values are slightly higher compared to the earlier years (2017-2019), indicating a mild increase in deviation from benchmark returns. Notably, the market experienced excessive tracking error indicating benchmark discrepancies and hinting individual stock selecting of the fund managers, during periods of volatility, such as 2015, 2019, and 2020. Alas, in reality the Indian mutual fund industry marginally to outperform in these volatility years despite of not following the benchmark.

Figure-4: Average Semi Variance During Timeline



The fund's vulnerability to market fluctuations, as well as its potential for risk and return, can be better understood by comparing the portfolio beta to the benchmark. *Table-2* indicates average beta is lower that unity. Lower averages identified in the year 2015, 2019 and 2020 the bear years in Indian market.

Table-3: Distribution of Portfolio Betas Over Benchmark

Portfolio Beta Over Benchmark	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Top 20%	90	82	101	81	106	179	110	135	192	184
Next 20%	53	75	45	**107**	**85**	19	28	1	19	26
Middle 20%	28	31	53	21	26	20	**78**	**80**	7	8
Lower 20%	1	1	1	3	1	0	2	2	0	0
Bottom 20%	0	0	1	0	0	0	0	0	0	0

The portfolio beta analysis suggests that fund managers were actively adjusting their portfolios to manage risk and take advantage of market conditions during the bull markets of 2016, 2021, and 2022. The increase in average beta during these years indicates a higher level of risk-taking by fund managers, potentially in pursuit of higher returns. However, the shift towards riskier assets compared to the benchmark in 2016, 2021, and 2022 could also indicate a potential vulnerability to market downturns. The fact that a significant number of funds adjusted their beta to a lower category in 2019 and 2020 suggests a recognition of the increased market volatility and potential for a market collapse during those years.

To conduct a more detailed analysis, the entire range of beta values was divided into five levels (as shown in *Table-3*), and then the portfolio beta was calculated for each segment in each year. With the exception of 2016 and 2017, the majority of the fund's beta consistently remained in the top twenty-percent category, based on a brief examination of the beta compared to the benchmark. The average beta, which indicates the extent to which a portfolio deviates from the sector benchmark, decreased during 2016 and 2017. In the years 2018, 2021, and 2022, a higher proportion of funds were found in the top 20% category of beta, suggesting that they held riskier assets compared to the benchmark. In order to protect the portfolio value from a market collapse in 2019 and 2020, a significant number of funds adjusted their beta to a lower category.

However, during periods of market downturns, some fund managers deviate from the benchmark in an effort to beat the market. This deviation from the benchmark can lead to an increase in the idiosyncratic risk of the portfolio holdings. In the Indian mutual fund sector, the average idiosyncratic risk has been found to surpass the 5% threshold. This indicates that there is a significant level of idiosyncratic risk present in the portfolios of Indian mutual funds. This can be attributed to the fact that numerous fund managers have taken specific stock-related risks during market downturns.

Specifically, in the years 2014, 2015, 2019, and 2020, there was a notable spike in idiosyncratic risk within the Indian mutual fund sector. This suggests that during these years, many fund managers deviated from the benchmark and took on additional stock-specific risks in an attempt to generate higher returns. This pattern is further supported by the beta dispersion from the benchmark. Despite the increase in idiosyncratic risk during these periods, it is important to note that Indian fund managers generally demonstrate strong risk management capabilities and successfully meet their predefined goals. They are able to effectively manage the idiosyncratic risk within their portfolios and generate satisfactory returns for their investors.

Conclusion & Discussion

The efficiency of mutual fund managers in India is the subject of a 10-year longitudinal study being conducted by the current research. The study analyses annual performance over a period of ten years in order to identify any trends in the fund managers' investing choices. The knowledge gathered from this research will help investors make wise financial decisions and advance knowledge of fund manager behaviour in the Indian mutual fund sector.

The Average Return Difference over Benchmark (ARDB) analysis revealed that, except for the pandemic year, Nifty 50 consistently outperformed the mutual funds under consideration. The mutual funds' performance remained below 5% in nine out of ten instances, indicating a consistent underperformance. In the year 2015, the ARDB outperformed the market during a down-market phase, showcasing a rare exception. The CERB analysis highlighted a persistent declining trend over the past decade. While notable cumulative returns were observed in 2013, 2015, and 2019, the average cumulative returns in years like 2017 and 2021 remained relatively low, even during strong economic periods. The fund managers' performance seemed to respond slowly to major market movements, as evidenced by their inability to predict and react promptly to market trends in certain years, such as 2014, 2017, and 2021. The risk premium analysis demonstrated a significant positive correlation between risk-adjusted returns of the Nifty 50 and risk premiums. In specific years – 2014, 2017, and 2021 – the fund risk premiums outperformed the key market returns, indicating successful risk management and potentially superior fund performance in those years.

The ability of fund managers to control excess volatility was evident from the negative values in *Table-1*, which indicated that they successfully kept excess volatility below benchmark risk levels. Fund managers demonstrated skill in protecting investments during COVID-19 years, suggesting their focus on preventing excessive volatility to safeguard fund values. The average semi variance, representing the managed portfolio's downside risk, remained steady at 1%-2% over the evaluated period. Notably, the semi variance experienced a significant increase in 2020 (8.376%) due to the impact of the COVID-19 shock. Indian fund managers exhibited better investing decisions compared to the chosen benchmark, as indicated by tracking errors. Years of higher tracking error (2015, 2019, and 2020) coincided with market volatility, suggesting that managers were using riskier strategies with potential for higher rewards.

Portfolio beta, reflecting sensitivity to market movements, showed average values lower than unity (1). In bear years (2015, 2019, and 2020), average beta values were lower, indicating a more defensive stance. Bull markets (2016, 2021, and 2022) saw higher average beta values, indicating greater alignment with market trends. The dispersion of beta from the benchmark influenced portfolio holdings' idiosyncratic risk. Years with higher idiosyncratic risk (2014, 2015, 2019, and 2020) suggested that fund managers made stock-specific bets during market downturns. The data indicated that Indian fund managers adeptly managed risk, adjusting beta and portfolio holdings to meet their objectives. Despite periods of market turbulence, the managers were able to achieve their goals.

In summary, the study's conclusions emphasize the difficulty of consistently outperforming benchmarks in the mutual fund context, while also shedding light on the Indian fund managers' prowess in risk management and adaptation to market dynamics. The ability to navigate challenges, protect investments, and make informed decisions underscores their competence in achieving competitive returns within a complex investment landscape.

References

Agarwal, S., & Mirza, N. (2017). A study on the risk-adjusted performance of mutual funds industry in India. *Review of Innovation and Competitiveness: A Journal of Economic and Social Research, III*(1), 75-94.

Ali, R., & Qudous, R. (2012). Performance evaluation of mutual funds in Pakistan. *Interdisciplinary Journal of Contemporary Research in Business, III*(9), 1076-1083.

Almonte, C. K. (2013). The risk-adjusted performance of equity and balanced funds in the Philippines. *International Journal of Information Technology and Business Management, XIV*(1), 49-64.

Avramov, D., & Wermers, R. (2006). Investing in mutual funds when returns are predictable. *Journal of Financial Economics, LXXXI*(2), 339-377. doi: https://doi.org/10.1016/j.jfineco.2005.05.010

Bilawal, M., Khan, M., Hussain, R., & Akmal, U. (2016). Performance evaluation of closed ended mutual funds in Pakistan. *International Journal of Management Business Research, VI*(1), 65-71.

Bollen, N. P., & Busse, J. A. (2001). On the timing ability of mutual fund managers. *The Journal of Finance, LVI*(3), 1075-1094.

Bollen, N. P., & Busse, J. A. (2005). Short-term persistence in mutual fund performance. *The Review of financial studies, XVIII*(2), 569-597.

Deb, S. G. (2019). Persistence in performance of actively managed equity mutual funds: New Indian evidence. *IIMB Management Review, XXXI*(2), 145-156. doi: https://doi.org/10.1016/j.iimb.2019.03.014

Deb, S. G., Banerjee, A., & Chakrabarti, B. B. (2007). Market timing and stock selection ability of mutual funds in India: An empirical investigation. *Vikalpa, XXXII*(2), 39-52.

Filip, D., & Karaś, D. (2019). Expense Ratio as an Effect of Fund Attributes' Impact. *Annales Universitatis Mariae Curie-Skłodowska, sectio H–Oeconomia, LII*(4), 17-27. doi: http://dx.doi.org/10.17951/h.2018.52.4.17-27

Goetzmann, W. N., Ingersoll, J., & Ivković, Z. (2000). Monthly Measurement of Daily Timers. *The Journal of Financial and Quantitative Analysis, XXXV*(3), 257-290. doi: https://doi.org/10.2307/2676204

Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *The Journal of Finance, XXIII*(2), 389-416. doi:https://doi.org/10.2307/2325404

Kiymaz, H. (2015). A performance evaluation of Chinese mutual funds. *International Journal of Emerging Markets, X*(4), 820-836. doi: http://dx.doi.org/10.1108/IJoEM-09-2014-0136

Koutsokostas, D., Papathanasiou, S., & Eriotis, N. (2018). Can mutual fund managers predict security prices to beat the market? The case of Greece during the debt crisis. *The Journal of Prediction Markets, XII*(3), 40-62. doi: https://doi.org/10.5750/jpm.v12i3.1644

Leite, P. A., & Cortez, M. C. (2009). Conditioning information in mutual fund performance evaluation: Portuguese evidence. *The European Journal of Finance, XV*(5-6), 585-605.

Low, S. (2012). Market timing and selectivity performance: A cross-sectional analysis of Malaysian unit trust funds. *Prague Economic Papers*, 205-219.

Mansor, F., Bhatti, M., & Ariff, M. (2015). New evidence on the impact of fees on mutual fund performance of two types of funds. *Journal of International Financial Markets, Institutions and Money, XXXV*, 102-115. doi: https://doi.org/10.1016/j.intfin.2014.12.009

Markowitz, H. (1959). *Portfolio Selection.* New York: John Wiley & Sons.

Menkhoff, L., & Schmidt, U. (2005). The use of trading strategies by fund managers: some first survey evidence. *Applied Economics, XXXVII*(15), 1719-1730. doi: https://doi.org/10.1080/00036840500217606

Nafees, B., & Shah, S. (2011). Performance evaluation of open end and close end mutual funds in Pakistan. *African Journal of Business Management*, 11425-11434.

O'Brien, T. J. (2020). Buy-and-Hold and Constant-Mix May Be Better Allocation Strategies Than You Think. *The Journal of Portfolio Management, XLVI*(6), 159-171. doi: https://doi.org/10.3905/jpm.2020.1.138

Pinnuck, M. (2003). An Examination of the Performance of the Trades and Stock Holdings of Fund Managers: Further Evidence. *Journal of Financial and Quantitative Analysis, XXXVIII*(4), 811-828. doi: https://doi.org/10.2307/4126744

Rao, Z. U., Tauni, M. Z., Ahsan, T., & Umar, M. (2020). Do mutual funds have consistency in their performance? *Portuguese Economic Journal, XIX*, 139-153. doi:https://doi.org/10.1007/s10258-019-00163-2

Riley, T. B. (2021, May). Portfolios of actively managed mutual funds. *The Financial Review, XLVI*(2), 205-230. doi: https://doi.org/10.1111/fire.12257

Ritesh, R. (2016). Analysis of performance of indices for Indian mutual funds. *Forging Connections between Computational Mathematics and Computational Geometry: Papers from the 3rd International Conference on Computational Mathematics and Computational Geometry*, 221-233. doi: https://doi.org/10.5176/2251-1911_CMCGS14.21_19

Sharpe, W. F. (1963). A Simplified Model for Portfolio Analysis. *Management Science*, 277-93.

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of business, XXXIX*(1), 119-138. doi: https://www.jstor.org/stable/2351741

Sharpe, W. F. (2013). The arithmetic of investment expenses. *Financial Analysts Journal, LXIX*(2), 34-41. doi: https://doi.org/10.2469/faj.v69.n2.2

Sortino, F. A., & Price., L. N. (1994). Performance measurement in a downside risk framework. *The Journal of Investing, III*(3), 59-64.

Tan, O. (2015). Mutual fund performance: Evidence from south Africa. *Emerging Markets Journal, V*(2).

Treynor, J. L. (1965). How to Rate Management of Investment Funds. *Harvard Business Review, XLIII*(1), 63-75.

Treynor, J. L., & Black, F. (1973). How to use security analysis to improve portfolio selection. *The Journal of Business, XLVI*(1), 66-86.

Tripathi, S., & Japee, D. G. (2020). Performance evaluation of selected equity mutual funds in India. *Gap Gyan-A Global Journal of Social Sciences*, 65-71.

Venugopal, M., & Sophia, S. (2020). Examining Sharpe Ratio, ASR, Sortino, Treynor and Info Ratio in Indian Equity Mutual Funds during the Pandemic. *International Journal of Management, XI*(11), 1267-1279. Retrieved from http://www.iaeme.com/IJM/issues.asp?JType=IJM&VType=11&IType=11

Wang, C. (2011). Why can managers time the market in issuing new equity? The global evidence. *Journal of Multinational Financial Management, XXI*(3), 151-164. doi: https://doi.org/10.1016/j.mulfin.2011.02.004

Wang, Y. A. (2017). Appraisal Ratio and the Mutual Fund's Stock Picking Skill. *Available at SSRN 3201993*.

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Financial Analysis of Domestic Systemically Important Banks (D-SIBs) in India: Bankometer and Zmijewski Models

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Abstract

RBI in its circular dated March 31, 2022 has categorized the private banks namely HDFC Bank and ICICI Bank, in addition to one public-sector lender State Bank of India as domestic systemically important banks (D-SIBs). The framework was issued by the country's central bank during July, 2014 in an attempt to publicly furnish the names of those Indian banks which are too big to fail and devoid of risks. The present paper examines the financial soundness of the three listed banks using the Bankometer and Zmijewski models for the period from 2014-15 to 2021-22. Both the models confirmed the three Indian banks as 'super-sound' and 'non-distressed' during the period under review, thus establishing the correctness of assessment made by RBI. The paper can be used as a reference by individuals and regulatory bodies to get an overview of the current health of the banks and take necessary remedial measures as applicable.

Keywords: Bankometer, Banks, Domestic, Non-distressed, SIBs, Super-sound, TBTF, Zmijewski

Introduction

The Reserve Bank of India (RBI) in a circular dated March 31, 2022 identified the private lenders ICICI Bank and HDFC Bank as well as State Bank of India (SBI) as 'Domestic Systemically Important Banks (D-SIBs)'. D-SIBs have been categorized as those financial institutions which are 'too big to fail' (TBTF) with an expectation to receive governmental support in times of distress and advantages in the financial markets. The framework for dealing with D-SIBs was issued by the country's banking regulator in 2014; with the banking entities being placed in appropriate buckets

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depending upon their systemic important scores (SISs). RBI had earlier announced SBI and ICICI Bank as D-SIBs in 2015 and 2016 respectively, with the latest entry being HDFC Bank. This comes as a welcome move for the Indian banking sector which has been grappled with insurmountable losses in recent times arising from increasing bad debts, rising inflation, war in Ukraine, and the Covid-19 pandemic.

The Indian banking industry has come under the scanner of the regulators in recent times owing to several instances of banking frauds and embezzlement of funds. Based on the RBI data, fraud cases involving Rs. 100 crores and above, both in cases of public and private commercial banks in India, has increased significantly over the years. This was further fuelled by the lack of data disclosure practices followed by the banks that has lead to a question over the authenticity of the published data. During the year 2022, state-owned State Bank of India (SBI) reported the country's biggest frauds totaling to Rs. 22,842 crore, by ABG Shipyard Company and its promoters. Earlier in the year 2023, the private-sector ICICI Bank has been involved in a bank loan fraud case following improper sanctioning of big-ticket loans to the Videocon Group during 2018, at the behest of Ms. Chanda Kochhar, the then chairman of the ICICI Bank. The number one private-sector lender HDFC Bank, based on market capitalization, has also been in the news for operational lapses and cyber-security issues leading to data theft and unauthorized transactions in the customer's account. Despite of such issues prevailing in the country's banking sector, HDFC Bank continues to enjoy the largest market share in the private banking industry followed by ICICI Bank. Among the public-sector commercial banks, SBI maintained its dominance with a largest market share among total deposits and credits.

In view of latest scams and operational issues pertaining to the country's three-best banking companies namely SBI, HDFC Bank and ICICI Bank, the study makes an attempt to review their past and present financial performances during the financial years from 2014-15 to 2021-22, following their recognition as risk-free banks. The study intends to examine the potentiality of the three banks to be recognized as D-SIBs. In this context, the present study has applied the Bankometer S-score (2000) coupled with the Zmijewski X-score model (1984) to review the past and present financial health of these three banks. The study covers a time span of 8 years ranging from 2014-15 to 2021-22 following the framework for D-SIBs issued by the banking regulator during July, 2014. The paper intends to assist the academicians, researchers, industry practitioners and policy-makers to check the financial progress of the country's three-largest banks as D-SIBs since 2014-15 and to take corrective actions and policy decisions for improvement.

The research paper is structured as follows: The following section discusses the previous studies related to the sector under review. Sample selection, research methodology and data sources have been presented next. The penultimate section narrates the findings and analyses of the study, followed by conclusion and recommendations. A list of references is given at the end for further readings.

Review of Literature

Different researchers attempted to discuss the financial solvency and bankruptcy prediction analyses of banking sector in India. For instance, Africa and Surabaya (2019) investigated the financial distress of 11 Islamic banks during 2014 to 2018. The 110 financial data was analyzed using the Bankometer model and the Logistic Regression model to assess the financial bankruptcy of Sharia banks in Indonesia. The results showed that both the Bankometer model and the RGEC model, (with respect to the variables NPL, GCG, ROA, and CAR), were recommended as a signaling strategy by Sharia banking industry in determining policies before the onset of bankruptcy so as to avoid liquidation of banks. Chakraborty (2022) analyzed the financial soundness through bankruptcy prediction of General Insurance Corporation of India, using Altman Z-score (1968), Springate (1978), Ohlson (1980) and Zmijewski (1984) models between the years 2016-17 to 2020-21. The study revealed that General Insurance Corporation of India was most likely to get into financial distress, in case the company financial health does not ameliorate in the near future. Shar et. al. (2010) examined the performance of Pakistani banks covering the time-period from 1999 to 2002 using the bankometer model. The results of Credit Leona's Securities Asia Stress test (CLSA-Stress test) and CAMELS test further authenticated the bankometer results, thereby indicating the latter's effectiveness. Ashraf and Tariq (2016) evaluated financial strength of banks listed on Pakistan Stock Exchange between the years 2006 to 2014. A total of 21 commercial banks listed on Pakistan Stock Exchange (PSX) were available during the study period. For comparison purpose, Fitch Bank-Scope and Z-score model was used for selection of banks listed on Pakistan Stock Exchange. These two models reported the same results, but however some were slightly different. Both the models found Bank of Punjab's financial soundness in the gray zone.

There is a scarcity of studies both in India and abroad that comprehensively examined the financial soundness and distress analysis of the domestic systemically important banks in India, in the light of banking frauds, rising non-performing assets and bank failures. The study intends to fill the research gap with a focus on the past and existing financial health of D-SIBs in India.

Research Methodology

Research Objectives

The study has two-fold objectives as given below:

- To investigate the financial soundness of domestic systemically important Banks during the period under review, using the Bankometer S-score index (2000)
- To predict the financial bankruptcy of domestic systemically important Banks during the period under review, using the Zmijewski X-score model (1984)

Sample Selection

The study considers sample size of three listed banking firms in India, based on the Reserve Bank of India (RBI) circular on the 'Framework for dealing with Domestic Systemically Important Banks (D-SIBs)' in India dated March 31, 2022. The three private lenders are ICICI Bank, HDFC Bank and the state-owned State Bank of India (SBI) has been listed as domestic systemically important banks in India for the financial year 2021-22. Although SBI and ICICI Bank maintained their status quo as risk-free banks since 2015, the latest addition being the HDFC Bank in 2021-22.

The D-SIB framework requires the Indian banking regulator to identify the names of public-sector and private sector commercial banks as systemically risk-free banks since the inception of the framework in 2014. The banks were placed in appropriate buckets depending upon their systemic importance scores (SISs), as calculated by RBI. Based on the risk buckets in which a D-SIB is placed, an additional common equity Tier 1 (CET-1) requirement needs to be maintained by the listed banks along with the capital conservation buffer.

Methodologies Used

Bankometer Model

The ratio-based Bankometer model (2000) is most popularly used to calculate the Solvency (S) scores to determine the financial efficiency of banks. The Bankometer model is based on financial ratios, similar to the CAMELS framework. The Bankometer model was recommended by IMF to investigate the financial strength of banking companies. The Bankometer model will help in gauging the solvency problems and to correct any shortcomings through appropriate channel. It can also be used by individuals and regulatory bodies to have a quick look over the banks' soundness.

$$\text{S-score} = 3.5\ CAR + 1.5\ CA + 1.2\ EA + 0.6\ NPL/Loan + 0.3\ CI + 0.04\ LA$$

The proxies of all six components and their parameters in the Bankometer model have been listed below in Table-1.

Table-1: Components of Bankometer Model

Components	Proxies	Parameters
CA	Capital (Tier-I)/Total Assets	CA > = 04%
EA	Owner's Equity/Total Assets	EA > = 02%
CAR	CAR (Tier 1 Capital + Tier 2 Capital)/Risk-Weighted Assets	40% = < CAR > = 08%
CI	Operating Expenses/Operating Income	CI =<40%
NPL/Loan	Non-Performing Loans to Total Loans	NPL/Loan =< 15%
LA	Loans to Total Assets	LA =<65%

Source: Ashraf and Tariq (2016)

Banks having solvency (S) scores above 70 are termed as super sound banks, while those banks having solvency scores below 50 are not solvent. Those banks having solvency scores between the range of 50 to 70 falls within gray area.

Zmijewski X-score Model (1984)

This model was developed in 1984 by Mark E. Zmijewski in a bid to forecast the likelihood of bankruptcy of a firm. The ratios used in the Zmijewski score were determined by the probit analysis that was applied to 40 distressed and 800 non-distressed companies in the US. The model provides a score, popularly known as X-score, for each specific company to differentiate between bankrupt and non-bankrupt businesses. It is a ratio-based model that uses a constant variable followed by three varied financial ratios to differentiate between distressed and non-distressed companies. These three accounting ratios have been weighted by the estimated coefficients in the X function, using the following equation:

$$\text{X-score} = -4.336 - 4.513X_1 + 5.679X_2 + 0.004X_3$$

Where, X_1 = Net Income to Total Assets; X_2 = Total Debt to Total Assets; and X_3 = Current Assets to Current Liabilities (Liquidity).

The composite X-score of a particular firm is compared against certain benchmark values, as proposed by Zmijewski in 1984, to predict the financial health of a firm. The benchmark value that has been applied in this model is 0 (Zero). A value of X-score below 0 (Zero) indicates “non-distressed firms“ that are unlikely to experience financial distress. On the flip side, a value of X-score above 0 (Zero) denotes “distressed firms“ that are likely to experience higher chances of bankruptcy in the immediate future (Hantono, 2019; Zmijewski, 1984).

Data Sources

The data for the present study has been obtained from the published financial statements of three domestic banks, with no emphasis on primary data. The period of the study is limited to 8 financial years from 2014-15 to 2021-22, following the framework for D-SIBs issued by the banking regulator during July, 2014.

Results and Discussion

Tables 2, 3 and 4 summarizes the financial performance indicators of the three D-SIBs across the study-period from 2014-15 to 2021-22, based on the Bankometer model, as recommended by IMF.

Table-2: Bankometer Results for HDFC Bank Ltd

	Per-cent-ages	40% =< CAR >= 08%	CA >= 04%	EA >= 02%	NPL/ Loan =< 15%	CI =< 40%	LA =<65%		
	Years	**CAR**	**CA**	**EA**	**NPL/ Loan**	**CI**	**LA**	**S-score**	**Status**
HDFC Bank Ltd.	**2014-15**	16.79	13.66	10.50	0.89	28.77	61.89	103.5	Super-sound
	2015-16	15.53	13.22	10.25	0.92	28.19	65.54	98.1	Super-sound
	2016-17	14.55	12.79	10.35	1.04	28.43	64.19	94.2	Super-sound
	2017-18	14.82	13.25	9.99	1.28	28.27	61.87	95.4	Super-sound
	2018-19	17.11	15.78	11.98	1.35	26.39	65.83	109.3	Super-sound
	2019-20	18.52	17.23	11.17	1.25	26.73	64.92	115.4	Super-sound
	2020-21	18.79	17.56	11.66	1.32	27.07	64.85	117.6	Super-sound
	2021-22	18.90	17.87	11.61	1.17	29.31	66.17	119.1	Super-sound

Source: Calculated

Table-3: Bankometer Results for ICICI Bank Ltd

	Per-cent-ages	40% =< CAR >= 08%	CA >= 04%	EA >= 02%	NPL/ Loan =< 15%	CI =<40%	LA =<65%		
	Years	**CAR**	**CA**	**EA**	**NPL/ Loan**	**CI**	**LA**	**S-score**	**Status**
ICICI Bank Ltd.	2014-15	17.02	12.78	12.44	1.40	36.8	59.97	107.9	Super-sound
	2015-16	16.64	13.09	12.45	2.67	34.7	60.39	107.2	Super-sound
	2016-17	17.39	14.36	12.95	4.89	35.8	60.15	114.1	Super-sound
	2017-18	18.42	15.92	11.96	4.77	38.8	58.28	119.5	Super-sound
	2018-19	16.89	15.09	11.23	2.06	43.56	60.82	111.9	Super-sound
	2019-20	16.11	14.72	10.61	1.41	43.50	58.75	107.4	Super-sound
	2020-21	19.12	18.06	11.98	1.14	37.20	59.63	122.6	Super-sound
	2021-22	19.16	18.35	12.08	0.76	40.51	60.86	124.1	Super-sound

Source: Calculated

Table-4: Bankometer Results for SBI

	Percent-ages	40% =< CAR >= 08%	CA >= 04%	EA >= 02%	NPL/ Loan =< 15%	CI =<40%	LA =<65%		
	Years	**CAR**	**CA**	**EA**	**NPL/ Loan**	**CI**	**LA**	**S-score**	**Status**
SBI	2014-15	12.00	9.60	6.27	2.12	49.04	63.47	82.4	Super-sound
	2015-16	13.12	9.92	6.12	3.81	49.13	62.08	87.6	Super-sound
	2016-17	13.11	10.35	6.95	3.71	47.75	58.06	88.6	Super-sound
	2017-18	12.60	10.36	6.34	5.73	50.18	56.01	87.9	Super-sound
	2018-19	12.72	10.65	6.00	3.01	55.7	59.38	88.5	Super-sound
	2019-20	13.06	11.00	5.87	2.23	52.46	58.84	88.7	Super-sound
	2020-21	13.74	11.44	5.59	1.50	53.6	54.02	91.1	Super-sound
	2021-22	13.83	11.42	5.61	1.02	53.31	54.81	91.1	Super-sound

Source: Calculated

The Bankometer results obtained for all the three banks showed an S-score well above 70 indicating them as highly solvent and 'Super sound' banks. The super-sound banks are those that are unlikely to fail and are financially sound. The private player HDFC bank registered an S-score above 100 in almost all the years, with exceptions being in the years from 2015 to 2018. The component-wise break-up of the bankometer index for HDFC Bank Ltd further displayed satisfactory results in line with their individual thresholds, with minor exceptions in few years. The other private player ICICI Bank Ltd also showed commendable scores with a composite S-score consistently above 100 across the period under review.

The component-wise break-up of the bankometer index for ICICI Bank Ltd were well within the given threshold limit and did not show any serious abnormality. Both the private lenders were classified as ‘super-sound’ banks based on their annual S-score beyond the threshold limit. For the state-owned State Bank of India (SBI), the composite value of S-scores lay within the range of 80 to 90, though beyond the threshold limit of 70. The scores of the public-sector lender were found to be lower than the private banks in the case of capital to total assets ratio and in equity to total assets ratio. In a nutshell, all the three banks fulfilled the composite S-score benchmark to be classified as ‘Super-sound banks’.

The Zmijewski X-scores have been further calculated for all the three banks, in a bid to confirm and cross-check their financial soundness and bankruptcy scores. Tables 5, 6 and 7 depicted the composite X-scores for all the three banking companies in India across the financial years from 2014-15 to 2021-22.

Table-5: Bankruptcy Prediction through Zmijewski X-score: Analysis of HDFC Bank

	Values	- 4.336	- 4.513	5.679	0.004	X-score	Status
	Years	Constant	X_1	X_2	X_3		
HDFC Bank Ltd.	2014-15		1.73	0.839	1.17	-7.37	Non-Distressed
	2015-16		1.73	0.845	1.12	-7.34	Non-Distressed
	2016-17		1.68	0.831	0.90	-7.19	Non-Distressed
	2017-18		1.64	0.857	2.62	-6.85	Non-Distressed
	2018-19		1.69	0.835	1.46	-7.21	Non-Distressed
	2019-20		1.71	0.844	1.31	-7.25	Non-Distressed
	2020-21		1.78	0.841	1.63	-7.58	Non-Distressed
	2021-22		1.78	0.843	1.80	-7.57	Non-Distressed

Source: Calculated

Table-6: Bankruptcy Prediction through Zmijewski X-score: Analysis of ICICI Bank

	Values	- 4.336	- 4.513	5.679	0.004	X-score	Status
	Years	Constant	X_1	X_2	X_3		
ICICI Bank Ltd.	2014-15		1.72	0.826	0.38	-7.41	Non-Distressed
	2015-16		1.34	0.831	0.49	-5.66	Non-Distressed
	2016-17		1.26	0.829	0.51	-5.31	Non-Distressed
	2017-18		0.77	0.848	0.51	-2.99	Non-Distressed
	2018-19		0.34	0.851	1.31	-1.03	Non-Distressed
	2019-20		0.72	0.852	1.58	-2.74	Non-Distressed
	2020-21		1.31	0.834	1.59	-5.51	Non-Distressed
	2021-22		1.65	0.832	2.34	-7.05	Non-Distressed

Source: Calculated

Table-7: Bankruptcy Prediction through Zmijewski X-score: Analysis of SBI

	Values	- 4.336	- 4.513	5.679	0.004	X-score	Status
	Years	**Constant**	**X_1**	**X_2**	**X_3**		
SBI	2014-15		0.68	0.870	1.12	-2.45	Non-Distressed
	2015-16		0.46	0.865	1.05	-1.49	Non-Distressed
	2016-17		-0.06	0.873	1.11	-3.82	Non-Distressed
	2017-18		-0.19	0.888	1.36	-1.56	Non-Distressed
	2018-19		0.02	0.900	1.83	-0.69	Non-Distressed
	2019-20		0.38	0.900	1.78	-0.93	Non-Distressed
	2020-21		0.48	0.903	1.93	-1.36	Non-Distressed
	2021-22		0.67	0.897	1.48	-2.25	Non-Distressed

Source: Calculated

In order to verify the authenticity of the bankometer test, Zmijewski model has been applied on the selected banks between the years 2014 to 2021 to test the solvency position of the respective banks. The composite X-scores of all the three firms were found to be less than the benchmark value of zero. A value of X-score below 0 (Zero) indicates "non-distressed firms" that are unlikely to experience financial distress. The negative X-scores of all the 3 banks further corroborate the fact that the banking companies were resilient and super-sound, with no signs of financial distress during the period under study. The scores for all the three banks under the Zmijewski model appeared to be consistent and reflected scores below the threshold limit of 0 (Zero) over the period under review.

Conclusion

The Bankometer and the Zmijewski X-score models were applied on each of the three listed Indian banks separately to evaluate their financial soundness. Both the models confirmed the banks as 'super-sound' and 'financially non-distressed' with no major indications of vulnerability during the period under review. Based on Bankometer scores, both private lenders namely HDFC Bank and ICICI Bank were found to be super sound with S-scores, above 100. The public-sector lender SBI also reported S-scores of above 80 across the period under review, much beyond the threshold limit '70'. Further, the result of the Zmijewski X-scores vividly supports the findings of the Bankometer model since all the three banks were found to be non-distressed, with negative scores below the threshold level of '0' (zero). Hence, the top financially sound banks were SBI, HDFC Bank and ICICI Bank which further justifies their selection as domestic systemically important banks by the RBI. Thus, the study would serve the policy-makers in devising plans, policies and strategies to address and mitigate the solvency issues in the Indian banking sector.

References

'A Framework for dealing with Domestic Systemically Important Banks', Basel Committee on Banking Supervision, October 2012, Bank for International Settlements (BIS), https://www.bis.org/publ/bcbs233.pdf

Africa, L. A. and Surabaya, S. P. (2019). 'Determination of Bankometer and RGEC Models to Predict Financial Distress on Sharia Banks in Indonesia.' *Proceedings of the 1st International Conference on Business, Law and Pedagogy*, ICBLP 2019, 13-15 February 2019, Sidoarjo, Indonesia

Ashraf, A. and Tariq, Y. B. (2016). 'Evaluating the Financial Soundness of Banks: An Application of Bankometer on Pakistani Listed Banks.' *The IUP Journal of Financial Risk Management*, XIII (3), 47-63.

Chakraborty, J. (2022). 'Financial Distress Analysis using Altman, Springate, Zmijewski and Ohlson Models: A Study on Indian Reinsurance sector.' *Empirical Economics Letters*, Vol. 21 (Special Issue 3), 127-142.

Hantono, 2019, Predicting 'Financial Distress using Altman Score, Grover Score, Springate Score, Zmijewski Score (Case Study on Consumer Goods Company).' *Accountability*, 8 (1), 1-16.

HDFC Bank, Financial Results, https://www.hdfcbank.com/personal/about-us/investor-relations/financial-results

ICICI Bank, Annual Reports, https://www.icicibank.com/about-us/annual

'RBI releases 2020 list of Domestic Systemically Important Banks (D-SIBs)', Reserve Bank of India (RBI) Press Releases, dated Jan. 19, 2021, https://rbidocs.rbi.org.in/rdocs/PressRelease/PDFs/PR968C4791F86D3464A33A62207A46BA7EA10.PDF

RBI website, https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx

SBI, Annual Reports, https://sbi.co.in/web/corporate-governance/annual-report

'SBI, ICICI Bank & HDFC Bank continue to be systematically important banks: RBI', Published in The Statesman, Kolkata dated 3rd January, 2023 (New Delhi), https://www. epaper.thestatesman.com/3641320/Kolkata-The-Statesman/04TH-JANUARY-2023#page/8/2

Shar, A. H., Shah, M.A., and Jamali, H. (2010). 'Performance Evaluation of Banking Sector in Pakistan: An Application of Bankometer.' *International Journal of Business and Management*, 5 (9), 81-86.

Zmijewski, M. E. (1984). 'Methodological Issues Related to the Estimation of Financial Distress Prediction Models'. *Journal of Accounting Research*, 22, 59-82.

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Impact of Regulation on Social and Financial Performance of MFIs: Evidence from India

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Abstract

The purpose of the study is to examine if financial sustainability goals of Indian microfinance institutions (MFIs) are in conflict with the social objectives. The study also evaluates the impact of reforms directed mostly at regularizing Financial performance of the MFIs, after a major crisis that destabilized the Indian microfinance sector in 2010. A non-parametric approach to frontier estimation, i.e., the Data Envelopment Analysis (DEA) based Malmquist productivity index is applied for evaluation of the change in performance of MFIs. A panel data set of 35 MFIs for ten years comprising of both non-banking financial companies (NBFC) MFIs and Non-NBFC MFIs has been used for the analysis. Results indicate that the reforms have contributed little towards improvement in social performance, though financial performance improved during post-reform. Detailed analysis suggests that striving for financial performance could compromise the social goals of MFIs. Further, the impact of the Indian microfinance crisis (2010) is evident, resulting in a productivity decline during and just after the crisis period. Additionally, it is seen that the Non-NBFC MFIs perform better than the more formal legal structure of NBFCs in both social and financial aspects of efficiency. This paper tries to fill the gap in the literature i.e. by assessing the impact of reforms on social and Financial performance of Indian MFIs and performance disparity across legal structure of MFIs.

Keywords: Financial Performance, India, Malmquist Productivity Index, Microfinance, Social Performance

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Introduction

The need for microfinance arises from the vast unbanked population deprived of basic financial services, i.e., credit. Microfinance Institutions (MFIs) bridge the gap by providing credit to that segment of society to whom banks find it costlier and unfeasible to serve. However, MFIs being a financial intermediary with social objectives, cannot sustain in the term without financial self-sufficiency, and in recent years, the double bottom-line approach of MFI's efficiency remained the fulcrum of academic research (Navin & Sinha, 2020; Hossain et al., 2020; Meyer, 2019; Roy & Pati, 2018). In the earlier stage, microfinance activities were carried out mostly by Non-Government Organizations (NGOs) with the help of grants and donations from various sources. As microfinancing scaled up, MFIs faced a fund crisis to sustain growth and thus moved to the commercial format (Sriram & Upadhyayula, 2004; Nair & Tankha, 2014).

The transition of microfinance from philanthropic organizations to commercial institutions and the possibility of mission drift have been widely debated in the literature (Bardhan et al., 2021, 2023; Lopattaet al., 2017; D'Espallieret al.,2017; Mersland & Strom, 2010; Sriram, 2010). In contrast, Tchakoute-Tchuigoua (2010) found that commercial MFIs are more socially efficient than non-profit MFIs. The mission drift of MFIs is the most debated topic in microfinance literature. The welfarists consider MFIs a social business providing financial services to people deprived of formal financial services. The institutionists argue that MFIs are only financial intermediaries(Brau & Woller, 2004). Though both approaches are centred on poverty reduction, they differ in terms of the MFI's delivery mechanism, target market and organizational structures and, consequently, on their efficiency level (Armendáriz & Morduch, 2005).

Academic literature on financial sustainability and social performance have a mixed view on the trade-off between financial and social performance of MFIs. A wide range of studies like Cull et al. (2007), Annim (2012), Louis et al.(2013), Lopattaet al. (2017) have supported the substitution hypothesis predicting trade-off between financial and social performance. According to these studies, serving the poorer clients requires huge cost and depth of outreach becomes a hindrance to be competitive in the market. Authors like Abate et al., 2013; Annim, 2012; Hermes et al., 2011 have shown that outreach is negatively associated with the cost efficiency of MFIs. Mahmood (2014), Cull et al. (2007) have shown optimal loan size has an impact on profitability of MFIs. Competition among MFIs for grant, donation and client has an adverse impact on social performance and negatively affects social performance (McIntosh & Wydick, 2005). In contrast, Kulkarni (2017), Gutierrez-Goiriaet al.(2016), Bassem (2012), and Gutiérrez-Nieto et al. (2009) found a positive correlation between financial and social efficiency and that social and financial performance are compatible with each other and are not substitute.

Past microfinance literature mostly focused on the social aspect of MFIs, like outreach to the poor and their impact on the borrowers, woman empowerment, financial inclusion. In recent decades researchers have also emphasized on the Operational aspect of MFIs as there is a shift in paradigm from subsidy-driven microlending to financially sustainable social business models (Hermes et al., 2011; Sriram & Upadhyayula, 2004) Financial goals are targeted at achieving financial self-sufficiency regarding recovering the cost of lending money to the financially deprived section. Other important contributing factors behind the increased focus on financial sustainability are the recent increase in competition among MFIs, commercialization of the sector and regulatory changes. However, in the quest of being sustainable, MFIs could be losing focus from their primary objective of social outreach (Hulme & Maitrot, 2014).

This paper tries to look at the difference in performance of MFIs which started as NGOs, Society, Trust, Not-for-Profit company (i.e., Non-NBFC MFIs) and the ones which started as NBFCs. Although some NGOs converted into NBFCs later, the mission and vision of these organizations did not change. The NGOs which converted into NBFCs did so to be able to expand and fulfil their social mission while NBFCs ventured into microfinancing when regulation reduced some of the market uncertainties.

Using data for 35 Indian MFIs, this study adds to the existing literature, by answering the following questions:

- Is there any perceptible difference in the social and Financial performance of Non-NBFC MFIs and NBFC MFIs?
- Is there any change in performance of the MFIs from before the reforms that followed the MFI crisis?

Rest of the paper is organized as follows: section 2 describes the Indian microfinance industry, the crisis that took place in 2010 and the reforms undertaken in response to the crisis. Methodology adopted in this paper has been described in section 3, results are presented in section 4 followed by discussion in section 5 and section 6 concludes.

MFIs in India

India is the most populous democracy in the world, with a population of 1.35 billion. As per the Global Multidimensional Poverty Indicator (MPI) report 2020, India ranked 62 among 107 countries with an MPI score of 0.123. Around 27.9 per cent of Indians are poor, out of which 36.8 per cent are from rural and 9.2 per cent are from urban areas. Around 191 million adults do not have access to a bank account, and 60 per cent of people do not have access to formal credit (The Global Findex Database, World Bank, 2017). Despite various efforts by the Government, financial inclusion remains a challenge (Ghosh, 2013).

Following the Grameen Bank model of Bangladesh, MFIs have emerged in India as an intermediary between the large banking network and the huge unbanked population. Microcredit is provided to SHGs (Self-Help Groups) or JLGs (Joint-Liability Groups) based on group lending or joint liability principle and social collateral helps women SHGs to access business loans from microfinance institutions for survival and growth of their businesses (Bongomin et al., 2020). MFIs are also involved in the activity of identifying prospective customers, creating groups, providing necessary training, granting loans and other services like insurance, and collecting loan instalments on a monthly, fortnightly or weekly basis. Presently, micro-credit is delivered through a variety of institutional channels, viz., scheduled commercial banks (SCBs), regional rural banks (RRBs), cooperative banks, NBFCs, Section 8 companies, and NBFC-MFIs as well as in other forms (Rao, 2021).

Microfinance as not for Profit Organization

Inspired by the success of Grameen Bank, many NGOs and private organizations started providing microloans to poor rural households. The increased access to rural finance led to poverty alleviation by providing special financial services to low-income groups and women. The success of SHG financing attracted grants, donations and subsidies from public authorities and other developmental organizations, and this turned out to be a philanthropic activity. Further, this drew interest of a larger number of NGOs to step into microfinance business (Morduch, 1999). The MFIs received huge funding directly through grants and donations or indirectly through soft-term loans from donors. However, the MFIs lacked institutional viability and were unable to cover their cost of operation. This prompted many MFIs to transform themselves into commercial institutions.

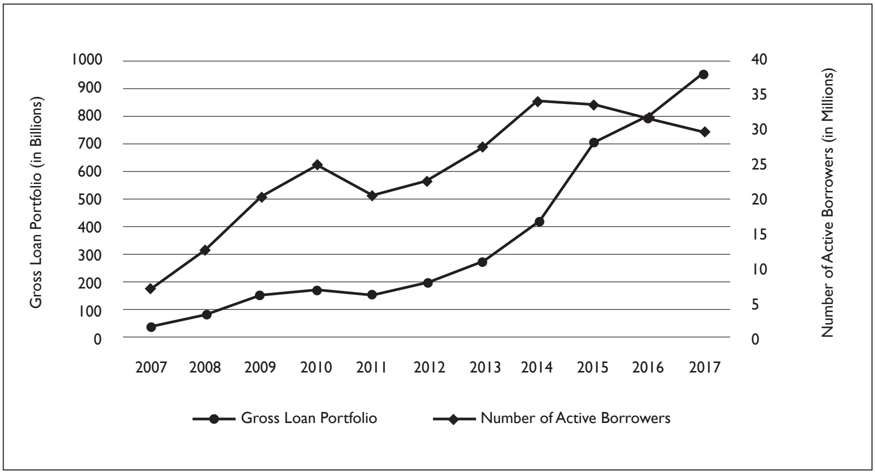
Microfinance as a Commercial Financial Institution

With the growth of microfinance, many foreign investment bankers have shown keen interest in microfinance. They created, acquired a company or registered as NBFC. Before the AP-microfinance crisis, the sector was unregulated in India. It prompted MFIs to expand without limits in an institutional vacuum (Nair, 2011). In order to meet the target profit and market share, MFIs focused more on the breadth of outreach and started serving the marginally poor and the non-poor. Thus, the social welfare objective of MFIs may have been compromised in the quest for profit and financial sustainability.

Crisis Period – The Andhra Crisis and Reforms

During the rise of microfinance in India, a shift from philanthropy to profit-making occurred, leading to a crisis in Andhra Pradesh characterized by mass defaults and reduced loan repayment rates due to over-lending and borrower overburdening. This crisis prompted the enactment of the Andhra Pradesh Microfinance Institutions (Regulation of Money Lending) Ordinance, 2010, which significantly restrained MFI operations, including home visits for loan collections and restricted issuance of fresh loans without government permission. The resultant mass default and cessation of loan repayment led to a significant decline in loan repayments to 60-70 per cent from 95 per cent in 2007-08, with an estimated outstanding default amount of ₹7,200 crores, of which 90 per cent remained unpaid. The crisis triggered significant pressure for regulatory reform, leading to the establishment of the Malegam Committee, which recommended measures to prevent over-lending, calling for the creation of a separate category for NBFC-MFIs. These reforms aimed to ensure sector stability, prevent over-lending, and enhance governance and operational practices within the microfinance sector. Situations like demonetization[], COVID-19 lockdown increased the loan delinquencies and had a negative impact on the financial efficiency of MFIs (Zheng & Zhang, 2020).

Figure-1: Growth in MFI's Gross Loan Portfolio and Number of Active Borrower



The present study attempts to do a comparative efficiency analysis of the MFIs in the pre and post reform periods. Also, the study investigates if there is any difference in performance between institutions operating as NBFCs and those operating as Non-NBFCs.

Research Methodology

Based on the objective of the study non-parametric DEA based Malmquist productivity index has been used to evaluate the efficiency scores of MFIs and change in efficiency during the pre and post crisis period for both types of legal structure. In this paper we have used output-oriented BCC model (Banker et al., 1984) for evaluation of Total Factor Productivity (TFP) change through Malmquist productivity index (MPI), with the assumption of variable returns to scale. The MPI produces three important parameters of efficiency changes, i.e. Technical Efficiency Change (TE), Technological Change (TC) and Total Factor Productivity Change (TFP), where TFP= TE * TC. Again TE is separated into pure technical efficiency (PTE) and scale efficiency (SE), where TFP= PTE * SE * TC (Färe et al., 1994).In the context of the Indian microfinance sector, technical efficiency change drives movement towards the efficient frontier, while technological change involves shifting the frontier due to advancements in technology. Pure technical efficiency reflects the ability of microfinance institutions (MFIs) to optimize output using the given level of input, while scale efficiency pertains to working at the optimal scale. Technological change in the microfinance service sector focuses on process innovation, such as improvement in regulatory regimes and the impact of macroeconomic variables, leading to better resource utilization by MFIs. Unlike technological change, which is generally positive over time, technological change may not always result in positive growth in efficiency and could potentially have adverse effects. (Detailed methodology explained in Appendix 3)

Table-1: List of Variables

Category	Input	Output
Financial Performance	Funds Employed	Financial Revenue
	Operating Expenses	Gross Loan Portfolio
Social Performance	Funds Employed	Number of Active Borrowers
	Personnel	Index of Poverty Reach(Pi)

Selection of Input and Output

Two input and two output variables are being used in this study to estimate the social and financial performance of MFIs (please refer Table-1). Following Sealey & Lindley (1977), the selection of variables is based on the production approach. As stated in Bardhan et al. (2023), variables are defined, and their units of measurement are represented in Table-2. The variables chosen are explained below:

Table-2: Description of Variables

Variables	Description	Unit of Measurement
Funds Employed (FEMP)	Debt and Equity (Long-term Funds)	INR[1]
Personnel (P)	Total Employee of the Organization	Number

1 INR= Indian Rupees

Variables	Description	Unit of Measurement
Operating Expenses (OPEXP)	Expenses towards business operation, including financing cost	INR
Gross Loan Portfolio(GLP)	Loan Outstanding from its borrowers	INR
Index of Poverty Reach(P_i)[2]	Derived index of Average loan outstanding	Index where $0 < P_i < 1$
Number of Active Borrowers (NAB)	Total number of active borrowers	Number
Financial Revenue (FREV)	Revenue generated from Interest and fee income	INR

Descriptive statistics for the above variables has been presented in Table-3. High standard deviation and range of variables denotes the diversity in size and scale of operation of Indian MFIs. Data and results have been elaborated in the following section.

Table-3: Descriptive Statistics of Variables

	Mean	Std. Dev.	Minimum	Maximum
FEMP (Millions)	10439.71	14835.15	22.8	59909.26
P	2819	4214	76	16357
OPEXP (Millions)	1404.07	2809.65	28.35	13097.4
GLP (Millions)	19473.28	33376.07	209.46	128081
Pi	0.53	0.25	0.00	1.00
NAB	984616	1576216	18818	6188000
FREV (Millions)	3356.82	6365.74	60.62	29784.4

Data and Results

The analysis in this paper focuses on Indian MFIs and is based on data collected from Mix Market and the World Bank Data Catalogue. Mix Market, an NGO based in the USA, provides a platform for sharing financial and social performance data of MFIs worldwide, collecting and standardizing data according to international standards. The data includes information on 92 Indian MFIs, filtered for those with four and five diamonds, which indicates a high level of transparency and reliability. To ensure the credibility of the data, it has been crosschecked with the annually published data by the MFIs. This study provides a comprehensive insight into the quality and reliability of data from Indian MFIs, crucial for understanding the microfinance landscape in India.

After eliminating MFIs with missing values, data for only 35 MFIs was considered out of which 18 are NBFCMFIs and 17 are Non-NBFC MFIs. Ten years' data from 2008 to 2017 have been taken for the study

2 Following Gutiérrez-Nieto et al.(2009) {P_i = 1 – ALB – Min(ALB)/Range of ALB}

as the recent data is unavailable. As stated in Table-1. two inputs and two outputs model is being used both for social and Financial efficiency thus, the sample size is considered to be adequate for conducting DEA analysis. To have a detailed inspection into the trend of efficiency the time frame has been classified into two groups i.e., 2008-2011 and 2011-2017 to know the impact of reforms after the crisis. Results presented in Table-4 and 5 shows the change in Financial and social performance respectively.

Financial Performance

Financial performance is mainly focused on the ability of MFIs to utilise the financial resources to generate revenue to be able to be financially sustainable. The analysis of microfinance institutions (MFIs) from 2008 to 2017 reveals significant shifts in financial performance and efficiency. During the initial period (2008-2011), there was an overall decline in financial productivity, with 14 out of 35 MFIs experiencing improved efficiency scores and the remaining 21 suffering declined scores(Table-4). Notably, NBFC MFIs like Utkarsh Microfinance and Uttarayan Financials faced substantial decreases in productivity, likely due to the global financial crisis. The post-crisis period (2011-2017) showed a remarkable improvement of approximately 40 per cent in financial performance, attributed to regulatory reforms. The majority of MFIs witnessed positive growth, largely influenced by technological advancements. However, technical efficiency change experienced a 5 per cent decrease, primarily due to a decline in pure technical efficiency (PTE)(See Figure-2).Increased competition in the sector may be considered as one of the contributing factors for low PTE. However, financial output has improved due to process innovation impacting the sector as a whole.

It's evident that Non-NBFC MFIs outperformed NBFC MFIs throughout the study period, with 3 per cent and 48 per cent growth during 2008-2011 and 2011-2017, respectively, in contrast to the declines and subsequent 34 per cent growth of NBFC MFIs. This stark difference can be ascribed to specific MFIs, such as BSFL, IDF Financial, Madura, Savodaya Nano, Smile, Utkarsh, and Uttarayan Financials, that were severely impacted by the crisis. The performance disparities align with global and Latin American findings Gutiérrez-Nieto et al.(2009) and D'Espallier et al. (2017), suggesting that MFI performance varies based on their NGO/NBFC status. Non-NBFC MFIs, benefiting from subsidies and grants, sustain minimum financing costs and demonstrate better financial performance, potentially due to their cost-saving management structures. The findings underscore the impact of regulatory measures and technological advancements on the financial outcomes of MFIs. They also indicate the influence of institutional status, subsidies, and management practices on the financial performance of MFIs. These insights can inform future policymaking and strategic decisions within the microfinance sector.

Figure-2: Financial Performance of MFIs

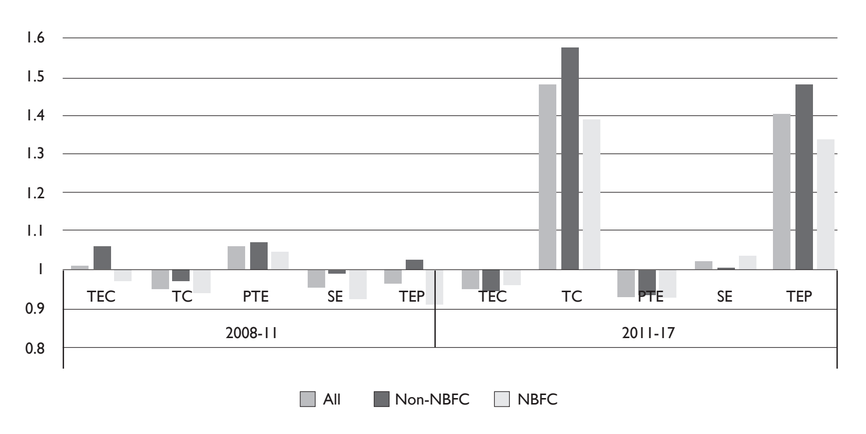


Table-4: MPI Scores on Financial Performance of MFIs

MFIs	2008-2011					2011-2017				
	TEC	TC	PTE	SE	TFP	TEC	TC	PTE	SE	TFP
ADK	1.192	0.928	1.247	0.955	1.106	0.940	1.332	0.919	1.022	1.252
ARH	0.776	1.142	0.926	0.838	0.886	1.255	1.540	1.121	1.120	1.933
ASA	0.993	0.977	1.190	0.834	0.970	1.267	1.240	1.054	1.202	1.570
ASIR	1.240	0.994	1.298	0.955	1.233	1.047	1.280	1.087	0.963	1.341
ASO	0.894	0.798	0.863	1.037	0.714	0.729	1.742	0.807	0.903	1.270
BELG	1.378	0.980	1.178	1.170	1.351	0.722	1.233	0.865	0.834	0.890
BFIL	0.845	1.112	1.000	0.845	0.940	1.418	1.527	1.000	1.418	2.165
BSFL	0.706	1.178	0.982	0.718	0.831	1.948	3.041	1.111	1.753	5.923
BWDA	1.331	0.873	1.300	1.024	1.162	0.501	1.355	0.579	0.865	0.679
CPOR	1.000	0.996	1.000	1.000	0.996	0.681	1.248	0.723	0.942	0.850
CHYA	2.036	0.996	2.049	0.994	2.028	0.985	1.512	0.975	1.010	1.490
CAG	1.067	0.977	1.032	1.034	1.042	1.026	1.411	1.000	1.026	1.448
GUFSL	0.852	1.023	0.858	0.993	0.872	0.855	1.748	0.986	0.867	1.494
IDFF	1.063	0.897	0.991	1.073	0.954	0.732	1.218	0.793	0.923	0.891
ICML	1.030	0.967	1.287	0.801	0.996	0.899	1.414	0.952	0.944	1.272
JANL	0.906	1.108	1.025	0.883	1.003	1.492	1.977	1.314	1.136	2.950
MDRA	0.987	0.846	1.000	0.987	0.835	0.799	1.212	0.814	0.982	0.968
MAHA	1.000	1.162	1.000	1.000	1.162	0.767	1.220	0.787	0.974	0.935
MSKT	1.227	0.920	1.259	0.975	1.129	0.919	1.974	1.000	0.919	1.814
NEED	1.106	0.902	1.113	0.993	0.997	0.823	1.372	1.064	0.773	1.129
RGVN	1.103	0.853	1.110	0.994	0.941	1.175	1.198	1.164	1.009	1.408
SUWS	0.828	0.933	0.847	0.978	0.773	0.755	1.227	0.800	0.943	0.926
SAIJ	0.962	1.130	1.242	0.775	1.087	0.933	1.680	0.602	1.549	1.568
SAMS	1.012	1.022	0.983	1.029	1.034	0.919	1.350	0.919	1.001	1.241
SANG	1.084	0.919	1.002	1.082	0.997	0.756	1.125	0.801	0.944	0.850

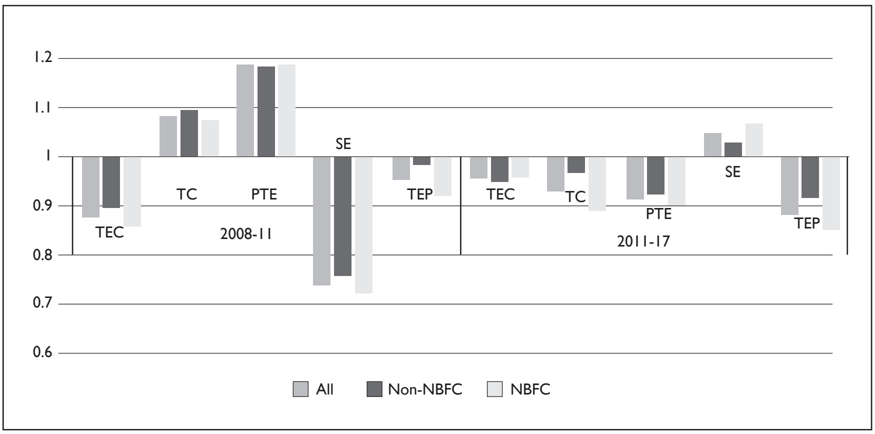
MFIs	2008-2011					2011-2017				
	TEC	TC	PTE	SE	TFP	TEC	TC	PTE	SE	TFP
SNANO	0.885	0.768	0.887	0.997	0.680	0.692	1.234	0.813	0.851	0.854
SATIN	1.450	0.904	1.346	1.077	1.311	0.650	1.375	0.753	0.862	0.894
SKDRDP	1.206	0.896	1.000	1.206	1.080	1.000	3.915	1.000	1.000	3.915
SMILE	0.800	0.963	0.972	0.823	0.771	1.077	1.234	0.890	1.209	1.329
SONA	0.863	0.916	0.878	0.984	0.791	0.992	1.214	0.980	1.013	1.205
SSF	0.898	0.893	1.000	0.898	0.802	1.114	2.517	1.000	1.114	2.803
UJJI	0.932	0.982	1.311	0.710	0.915	1.122	1.487	0.812	1.382	1.668
UTKR	0.718	0.833	0.725	0.991	0.599	1.107	1.382	1.210	0.915	1.530
UTRN	0.717	0.833	0.717	1.000	0.597	1.394	1.403	1.394	1.000	1.955
VILL	1.363	0.894	1.360	1.002	1.218	1.035	1.237	1.013	1.022	1.279
Mean	1.015	0.952	1.063	0.955	0.966	0.950	1.481	0.929	1.023	1.408

Source: Author's computation

Social Performance

Table-5 represents the indices of TFP from 2008 to 2011 and 2011 to 2017. It is evident from the result that although overall social efficiency has decreased in both pre and post-crisis period, average efficiency of Non-NBFC MFIs stood higher than the NBFC MFIs. MFIs like CHYA, IDFF, SNANO had gone through downsizing of business and withdrew operation from few areas leading to decrease in number of active borrowers. One of the major contributing factors for decreased social performance is increased ticket size of the loan, which means more focus on well-off borrowers. Moreover, average loan balance (ALB) has increased by more than 2.3 times during post reform period.

Figure-3: Social Performance of MFIs



During the period 2008-11 there was on an average 5 per cent decline in social performance out of which NBFC MFIs showed a decline of 8 per cent while NGOs showed a 2 per cent of reduction (Please refer to Figure-3). These regress in social performance are found to continue in the post-crisis period from 2011 to 2017 where social performance of NBFC MFIs reduced by 15 per cent and that of Non-NBFC MFIs by 8 per cent. While analysing the post-crisis social performance, it is observed that the crisis had a negative impact on the social performance of most Indian MFIs. There were 24 MFIs whose performance declined during the post-crisis period, and only 11 MFIs had positive growth. The pre-reform period can be characterized by high PTE, marginal increase in TC and low scale efficiency; on the contrary, post-reform social efficiency can be seen as an outcome of a marginal increase in scale efficiency due to an increase in client base by about 2.4 times.

Table-5: Social Performance of MFIs

MFI	2008-2011					2011-2017				
	TEC	TC	PTE	SE	TFP	TEC	TC	PTE	SE	TFP
ADK	0.989	0.997	1.042	0.949	0.986	0.668	0.888	0.625	1.069	0.593
ARH	0.473	1.215	0.806	0.587	0.575	0.993	1.056	0.738	1.345	1.049
ASA	0.855	1.018	1.247	0.686	0.870	1.239	1.072	0.850	1.457	1.328
ASIR	1.300	1.209	1.948	0.667	1.571	0.687	1.013	0.895	0.767	0.696
ASO	0.537	0.885	0.549	0.977	0.475	1.101	0.879	0.973	1.132	0.968
BELG	1.651	0.985	2.476	0.667	1.626	0.680	0.495	0.744	0.914	0.337
BFIL	0.428	1.297	1.000	0.428	0.555	0.789	1.284	1.000	0.789	1.013
BSFL	0.376	1.276	0.721	0.521	0.479	2.008	3.259	1.128	1.781	6.545
BWDA	0.965	1.023	1.156	0.835	0.986	0.900	0.745	0.786	1.145	0.671
CPOR	1.526	1.035	2.218	0.688	1.579	0.630	1.069	1.012	0.622	0.673
CHYA	2.616	1.194	2.748	0.952	3.124	0.719	0.876	1.069	0.673	0.630
CAG	0.737	1.400	1.154	0.639	1.032	0.959	0.895	0.904	1.060	0.859
GUFSL	0.342	1.159	0.446	0.767	0.396	1.037	0.907	0.868	1.195	0.941
IDFF	0.855	0.903	0.875	0.978	0.772	0.448	0.855	0.404	1.108	0.383
ICML	0.732	1.179	1.546	0.474	0.863	1.000	0.437	1.000	1.000	0.437
JANL	1.982	1.421	2.471	0.802	2.818	1.353	1.100	1.565	0.864	1.488
MDRA	0.649	0.901	0.814	0.797	0.584	1.146	0.968	0.707	1.621	1.109
MAHA	1.543	1.309	1.585	0.973	2.020	0.758	0.873	0.833	0.910	0.662
MSKT	1.115	0.949	1.847	0.604	1.058	0.808	0.770	0.805	1.004	0.622
NEED	1.117	0.958	1.198	0.932	1.070	1.136	0.761	0.970	1.171	0.865
RGVN	0.937	1.003	1.173	0.799	0.940	1.469	0.840	1.311	1.121	1.234
SUWS	0.687	0.961	0.832	0.826	0.660	1.187	1.121	1.210	0.981	1.330
SAIJ	1.770	1.505	1.775	0.997	2.663	0.569	0.725	0.749	0.761	0.413
SAMS	1.670	1.090	1.710	0.976	1.819	0.924	0.743	0.836	1.105	0.686
SANG	1.000	1.242	1.000	1.000	1.242	1.000	0.692	1.000	1.000	0.692
SNANO	0.693	0.770	0.738	0.939	0.534	0.787	1.201	1.019	0.772	0.945
SATIN	1.005	1.216	1.915	0.525	1.223	0.918	0.878	0.981	0.936	0.806
SKDRDP	1.108	0.947	1.000	1.108	1.048	2.610	1.631	1.924	1.357	4.259
SMILE	0.555	1.176	1.055	0.526	0.653	1.262	0.917	1.092	1.156	1.157

MFI	2008-2011					2011-2017				
	TEC	TC	PTE	SE	TFP	TEC	TC	PTE	SE	TFP
SONA	0.863	1.003	1.209	0.713	0.865	1.019	0.939	0.989	1.030	0.957
SSF	0.523	1.143	1.000	0.523	0.598	0.876	0.858	0.735	1.192	0.752
UJJI	1.495	1.240	2.928	0.511	1.853	1.251	1.073	1.237	1.011	1.343
UTKR	0.428	0.891	0.514	0.832	0.381	0.934	0.908	0.854	1.094	0.848
UTRN	0.404	0.816	0.480	0.840	0.330	0.739	0.809	0.730	1.011	0.597
VILL	0.964	1.055	1.423	0.678	1.017	0.857	0.889	0.604	1.419	0.762
Mean	0.877	1.082	1.185	0.740	0.949	0.954	0.926	0.912	1.046	0.883

Source: Author's computation

Performance and Legal Status of MFIs

Table-6 shows the summary of means, long-term change in efficiency from 2008 to 2011 and 2011 to 2017 representing pre and post-crisis performance change. The results indicate that the efficiency level of Non-NBFC MFIs were better than NBFC MFIs in both Financial and social performance. During 2008 to 2011 there was positive growth in Financial performance of Non-NBFC MFIs while NBFC MFI's performance fell by 9 per cent. However, in aggregate NBFC MFIs performed better in Financial frontier than social frontier.

It revealed that the socially efficient firms were mostly NGOs, while NBFC MFIs showed a decrease in efficiency post-reform, possibly due to the need to improve financial performance affecting social performance. The reform created an environment conducive to resource utilization, leading to overall technological change and process improvements in the sector. However, the social performance marginally declined after the reform, mainly due to reduced technical efficiency. The restructuring post-reform may have posed challenges for firms to catch up with the best practices among peers. These findings align with similar research on MFIs in African, Asian, and Latin American regions (Haq et al., 2010). Furthermore, the year-on-year change in financial and social performance was presented visually to illustrate the trends in Figure-4. and Figure-5.

Figure-4: YoY Change in Financial Efficiency

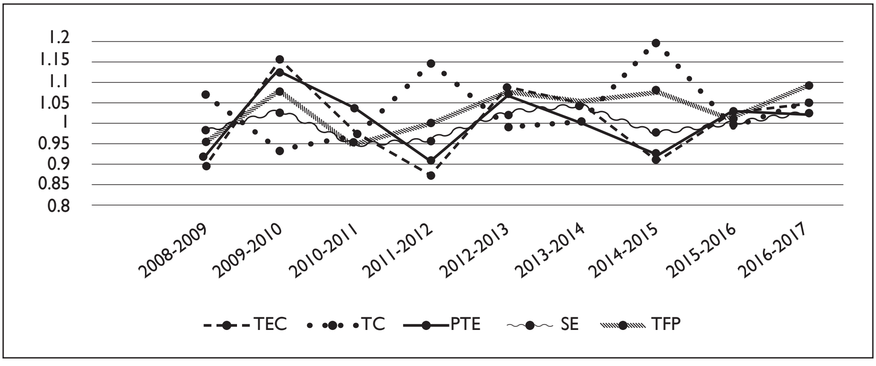


Figure-5: YoY Change in Social Efficiency

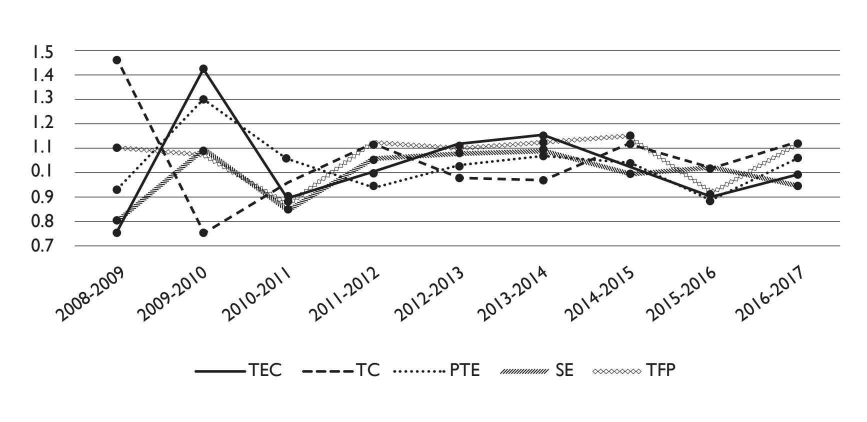


Table-6: Malmquist Index Summary of Firm Means

	Financial									
	2008-11					2011-17				
	TEC	TC	PE	SE	TFP	TEC	TC	PE	SE	TFP
All	1.015	0.952	1.063	0.955	0.966	0.95	1.481	0.929	1.023	1.408
Non-NBFC	1.063	0.97	1.075	0.988	1.031	0.94	1.578	0.932	1.008	1.483
NBFC	0.971	0.936	1.051	0.924	0.909	0.96	1.395	0.926	1.037	1.34

	Social									
	2008-11					2011-17				
	TEC	TC	PE	SE	TFP	TEC	TC	PE	SE	TFP
All	0.877	1.082	1.185	0.74	0.949	0.954	0.926	0.912	1.046	0.883
Non-NBFC	0.898	1.093	1.183	0.759	0.982	0.948	0.966	0.924	1.026	0.916
NBFC	0.858	1.072	1.187	0.723	0.92	0.959	0.889	0.900	1.065	0.852

Source: Author's computation

Discussion

The study conducted on Indian MFIs from 2008 to 2017 using the DEA Malmquist productivity index revealed interesting insights. It encompassed 35 MFIs and identified that Non-NBFCs outperformed NBFCs in both social and financial aspects, with an overall efficiency increase during the study period. Non-NBFC MFIs appeared to focus more on social aspects, while NBFCs prioritized financial efficiency, potentially compromising the social purpose of microfinance for-profit goals. This result is in line with Kaur (2016) in the context of Indian MFIs and Gutierrez-Goiriaet al. (2016) in a cross country study.

Post-crisis reforms aimed to enhance financial sustainability, transforming some MFIs into Small Finance Banks (SFBs). SFBs could take deposits, aiding financial sustainability while providing micro savings services to low-income households. Nonetheless, concerns arose regarding whether the social outputs of micro-savings adequately countered any social objective discount due to financial pressures (Morduch, 1999; Banerjeeet al*.,* 2015). However, further study may be needed to comment if the social output of micro-savings has been able to outweigh any discount on social objectives resulting from the pressure on these banks to achieve financial goals.

The shift in the Indian microfinance industry from outreach to profit was noted (Niar, 2010), necessitating sector transformation for discipline. As opined by Mr C S Ghosh, the CEO of Bandhan Bank, formerly Bandhan Microfinance, in an interview with the authors, "Technically NGO is not the right format to operate in, to cope with rapid expansion... to operate as a financial institution and to meet the requirements set by the apex regulatory organization like capital adequacy norm". He emphasized the incompatibility of operating as a Non-NBFC with rapid expansion requirements, advocating for NBFC registration to align with regulatory norms. However, challenges persisted, particularly for commercial NBFCs influenced by foreign investments, where social commitment often played a secondary role.

Regulatory impacts post-crisis showed positive financial growth for MFIs but decreased social efficiency. Analysis indicated higher performance by Non-NBFC MFIs in both social and financial dimensions, while NBFCs excelled in operational efficiency but lagged in social goal attainment. Despite a 48 per cent rise in financial performance post-crisis, social performance declined by approximately 12 per cent, affecting over 70 per cent of MFIs. The study emphasized the importance of balancing social and financial goals with reforms enhancing transparency and stability without compromising social objectives. Regulatory measures should not overlook the social missions of MFIs amidst the push for financial sustainability.

Conclusions and Limitations

After the AP microfinance crisis, reforms tightened regulations for NBFC MFIs, enhancing financial performance but potentially compromising their primary goal of serving the poor. The government needs to support financially self-sufficient and socially efficient NGOs to maintain this crucial balance. While regulations aim to bring consistency and discipline, nuanced approaches are necessary to uphold the welfare-focused nature of MFIs. It is important to prioritize efficiency in lending, stakeholder protection, transparency, and inclusive monitoring beyond just financial metrics. The availability of the data is one of the major limitations of this study, which limits the duration of the study up to 2018. Moreover,the focus has been largely on quantitative efficiency. Yet, qualitative studies are essential for a comprehensive understanding, emphasizing aspects like group lending, social capital creation, and positive spill-over effects on social well-being, education, health, and local economies. Future research should also measure the broader social impacts of MFIs to capture their contributions to various social indicators in the regions they operate.

References

Abate, G. T., Borzaga, C., & Getnet, K. (2013). Cost-Efficiency and Outreach of Microfinance Institutions: Trade-Offs and The Role of Ownership. *Journal of International Development*, 26(6), 923-932.

Annim, S. K. (2012). Microfinance efficiency: trade-offs and complementarities between the objectives of microfinance institutions and their performance perspectives, *The European Journal of Development Research*. 24(5), 788-807.

Armendáriz, B., & Morduch, J. (2005). *The economics of microfinance*, MIT Press, London.

Banerjee, Abhijit. Karlan, Dean. Zinman, Jonathan. (2015). Six Randomized Evaluations of Microcredit: Introduction and Further Steps, *American Economic Journal: Applied Economics*. 7(1), 1-21.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*. 30(9), 1078-1092.

Bardhan, A. K., Nag, B., Mishra, C. S., & Tarei, P. K. (2021). An integrated framework for analysing performance indicators of Indian microfinance institutions: a multi-stakeholder perspective. Benchmarking: An International Journal, 28(9), 2711-2740.

Bardhan, A. K., Nag, B., & Mishra, C. S. (2023). Microfinance Institutions' Efficiency and its Determinants: Evidence from India. South Asia Economic Journal, 24(2), 109-136.

Basher, M. A. (2007). Empowerment of microcredit participants and its spillover effects: evidence from the Grameen Bank of Bangladesh. *The Journal of Developing Areas*, 40, 2, 173-183.

Bassem, B. S. (2012). Social and financial performance of microfinance institutions: Is there a trade-off? *Journal of Economics and International Finance*. 4(4), 92-100.

Bongomin, G.O.C., Woldie, A. and Wakibi, A., (2020). Microfinance accessibility, social cohesion and survival of women MSMEs in post-war communities in sub-Saharan Africa: Lessons from Northern Uganda, *Journal of Small Business and Enterprise Development*. 27(8) 749-774.

Brau, J. C., & Woller, G. M. (2004). Microfinance: A Comprehensive Review of the Existing Literature, *The Journal of Entrepreneurial Finance & Business Ventures*. 9(1), 1-28.

Cull, R., Demirguz-Kunt, A. & Morduch, J. (2007). Financial performance and outreach: a global analysis of lending microbanks, *Economic Journal*. 117, 107-133.

D'Espallier, B., Goedecke, J., Hudon, M., & Mersland, R. (2017). From NGOs to banks: Does institutional transformation alter the business model of microfinance institutions? *World Development*. 89, 19-33.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries, *The American economic review*. 66-83.

Ghosh, Jayati. (2013). Microfinance and the challenge of financial inclusion for development, *Cambridge Journal of Economics*. 37(6), 1203-1219.

Gutiérrez-Nieto, B., Serrano-Cinca, C., & Mar Molinero, C. (2009). Social efficiency in microfinance institutions, *Journal of the Operational Research Society*. 60(1), 104-119.

Haq, M., Skully, M., & Pathan, S. (2010). Efficiency of microfinance institutions: A data envelopment analysis, *Asia-Pacific Financial Markets.* 17(1), 63-97.

Hermes, N., & Hudon, M. (2018). Determinants of the performance of microfinance institutions: A systematic review, *Journal of Economic Surveys*. 32(5), 1483-1513.

Hermes, N., Lensink, R., & Meesters, A. (2011). Outreach and Efficiency of Microfinance Institutions, *World Development*. 39(6), 938-948.

Hulme, D., & Maitrot, M. (2014). Has Microfinance Lost its Moral Compass? *Economic and Political Weekly*. XLIX(48), 77-85.

Kaur, P. (2016). Efficiency of Microfinance Institutions in India: Are They Reaching the Poorest of the Poor? *Vision*. 20(1), 54-65.

Khandker, S. R. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh, *World Bank Economic Review*. 19(2), 263-286.

Kulkarni, L., (2017). Financial efficiency versus social outreach of Indian microfinance institutions: mission drift or character shift? *Journal of Social and Economic Development*. 19(2), 323-340.

Lebovics, M., Hermes, N., & Hudon, M. (2016). Are financial and social efficiency mutually exclusive? A case study of Vietnamese microfinance institutions, *Annals of Public and cooperative Economics*. 87(1), 55-77.

Lopatta, K., Tchikov, M., Jaeschke, R., & Lodhia, S. (2017). Sustainable Development and Microfinance: The Effect of Outreach and Profitability on Microfinance Institutions' Development Mission, *Sustainable Development*. 25(5), 386-399.

Louis, P., Seret, A., & Baesens, B. (2013). Financial efficiency and social impact of microfinance institutions using self-organizing maps, *World Development*. 46, 197-210.

Mahajan, V., & Navin, T. (2013). Microfinance in India: Lessons from the Andhra Crisis, In *Microfinance 3.0: Reconciling sustainability with social outreach and responsible delivery*. Springer. Berlin, Heidelberg. 1-12.

McIntosh, C., & Wydick, B. (2005). Competition and microfinance, *Journal of Development Economics*. 78(2), 271-298.

Mersland, R., & Strøm, R. Ø. (2010). Microfinance mission drift? *World Development*. 38(1), 28-36.

Mia, M. A., & Soltane, B. I. B. (2016). Productivity and its determinants in microfinance institutions (MFIs): Evidence from South Asian countries, *Economic Analysis and Policy*. 51, 32-45.

Morduch, J. (1999). The Microfinance Promise, *Journal of Economic Literature*. 37(4), 1569-1614.

Nair, T. S. (2011). Microfinance: Lessons from a crisis, *Economic and Political Weekly.* XLVI(6), 23-26.

Nair, T. S. (2010). Commercial microfinance and social responsibility: a critique, *Economic and Political Weekly*. XLV(31), 32-37.

Nair, T and Tankha, A. (2014). *Microfinance India*, *State of the sector Report 2013*, Sage Publication, New Delhi.

R, Rao. (2021). Micro finance: Empowering a Billion Dreams, Sa-Dhan National Conference on Revitalizing Financial Inclusion, October 27, 2021, India.

Sealey, C. W., & Lindley, J. T. (1977). Inputs, Outputs, and a Theory of Production and Cost at Depository Financial Institutions, *The Journal of Finance*. 32(4),1251-1266.

Sriram, M. S. (2010). Commercialisation of microfinance in India: a discussion of the Emperor's apparel, *Economic and Political Weekly*. XLV(24), 65-73.

Sriram, M. S., & Upadhyayula, R. S. (2004). The Transformation of the Microfinance Sector in India, *Journal of Microfinance*. 6(2), 89-112.

Tchakoute-Tchuigoua, H. (2010). Is there a difference in performance by the legal status of microfinance institutions? *The quarterly review of economics and finance*. 50(4), 436-442.

World Bank. (2017). The Global Findex Database 2017, Washington, DC Available at: https://www.worldbank.org/en/news/press-release/2018/04/19/financial-inclusion-on-the-rise-but-gaps-remain-global-findex-database-shows (Accessed 19 February 2020)

World Bank. (2019). Poverty and Equity report, Available at: http://povertydata.worldbank.org/poverty/region/SAS(Accessed 19 February 2020)

Zheng, C., & Zhang, J. (2020). The impact of COVID-19 on the efficiency of microfinance institutions, *International Review of Economics & Finance*. 71, 407-423.

Endnotes

Financial Performance and Operational Performance is being used interchangeably.

On 8th November 2016 Government of India demonetized INR 500 and 1000 notes.

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On-the-Spot Decision Making: A Bibliometric Investigation into Impulse Buying Research Progression, Network Structures and Emerging Trends

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Abstract

The objectives of the current study are to synthesize existing literature on impulse buying, track its development over time, analyse intellectual and social structure based on this synthesis, and propose cluster-based themes for future research in the domain of impulse buying. A framework-based bibliometric review, as proposed by Donthu et al. (2021), utilized the Clarivate Web of Science and Scopus for literature retrieval. For descriptive and network analysis, researchers employed the Biblioshiny web application in R, enabling the analysis and presentation of results in both tabular and graphical formats. Co-citation analysis revealed the intellectual structure of the bibliographic data in this research domain. This analysis identified four clusters, each delving into different aspects of impulse buying. These clusters encompassed discussions on consumer psychology, personality traits, the complexities of e-impulse buying from various perspectives, influencing stimuli of impulse buying behavior, consumer emotions, and theoretical & analytical insights associated with impulse buying. Additionally, it was illustrated through author collaboration network analysis that researchers investigated a range of topics including cultural influences, gamification, social endorsements, and sustainability practices to comprehend impulse buying and post-purchase behavior

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in various contexts. The study pioneers a novel approach by generating cluster-based themes through network analysis, offering valuable guidance for future research endeavors in the realm of impulse buying. Another innovative aspect lies in its utilization of both Scopus and Web of Science databases, reflecting a concerted effort to comprehensively synthesize literature and incorporate diverse perspectives and findings into the research.

Keywords: Bibliometric Analysis, Biblioshiny, Impulse Buying, Intellectual Structure, Social Structure

Introduction

Consumer behavior encompasses the intricate processes involved in acquiring products or services, including decision-making before and after these actions (Rodrigues et al., 2021). Recent years have witnessed significant shifts in consumer decision-making, reshaping their purchasing intentions. With marketplaces characterized by fierce competition and continuous innovation in products and services, understanding customer needs has become paramount (Varadarajan, 2020). Examining the determinants that shape consumer behavior paves the way for innovative approaches to meet their evolving demands. This research is pivotal for marketers seeking to tailor campaigns effectively to their target audiences, fostering engagement and loyalty (Ding et al., 2020).

Impulse buying, often synonymous with on-the-spot decision making, stands as a captivating and extensively studied phenomenon within consumer behavior landscapes. This buying behavior has captured the attention of both researchers and businesses due to its profound implications for society, businesses, and individual consumers. Over time, diverse definitions and interpretations of impulse buying have emerged. In its narrowest sense, impulse buying refers to "a sudden and immediate purchase without prior shopping intentions, driven by an urge and characterized by spontaneity and minimal reflection" (Obukhovich & Sipilä, 2023). Impulse spending has seen a remarkable uptick, with a reported annual growth rate of 14% and 75% of consumers engaging in impulse purchases (Mandolfo & Lamberti, 2021). A multitude of studies have delved into this phenomenon to unravel its complexities. Understanding consumer behavior and activities in shopping environments is indispensable for marketers aiming to craft compelling unique selling propositions that captivate and persuade consumers to indulge in impulse buying.

Despite decades of research, impulse buying remains a pertinent theme in both academia and business, reflecting the evolving landscape of consumer behavior. Synthesizing past research findings is indispensable for advancing knowledge in this domain. Bibliometric methods serve as a valuable tool, enabling researchers to mobilise aggregated bibliographic data from the researchers and scholars, thereby offering invaluable insights into the field's structure, social networks, and topical interests (Zupic& Carter, 2015).

Rationale of the Study

Impulse buying, a widely researched phenomenon, has been subjected to systematic analysis in recent years. Notably, prominent literature reviews (e.g., Mandolfo & Lamberti, 2021; Redine et al., 2023; Xiao & Nicholson, 2013) and meta-analyses (e.g., Iyer et al., 2020; Santini et al., 2019) have predominantly focused on this concept. However, there exists a significant gap in systematically conceptualizing the outcomes and long-term ramifications of impulse buying (Redine et al., 2023). This gap is particularly crucial given the heightened interest in impulse buying outcomes in recent years, with over a third of studies emerging after 2020. Notably, existing studies have only covered data up to 2021. Therefore, our study endeavors to bridge this gap by extending the analysis to 2023, drawing insights from two esteemed databases: Scopus and Web of Science. The utilization of cluster-based themes derived from network analysis to explore the intellectual and social structures of impulse buying literature offer unique perspectives for future research in this field. Additionally, the incorporation of both Scopus and Web of Science databases enhances the novelty and comprehensiveness of our research synthesis. Thus, our study aims to: (1) Synthesize existing literature on impulse buying and track its evolutionary trajectory, (2) Develop intellectual and social structures based on literature synthesis, and (3) Propose cluster-based themes to guide future research endeavors in impulse buying for academics and researchers.

Research Questions

RQ 1: What is the historical progression of Impulse buying research?

RQ 2: What are the most prominent and actively growing keywords, documents and sources in the arena of Impulse buying?

RQ 3: How have networks of co-citations formed among published documents?

RQ 4: What kind of collaborations exist among authors and countries working in the field of Impulse buying?

Research Methodology

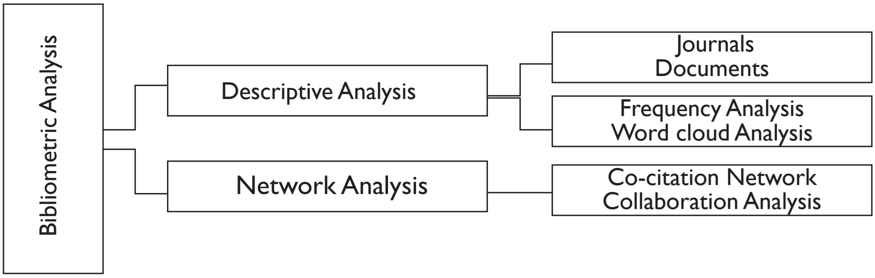
Data Collection

To achieve our objectives, we conducted a framework-based bibliometric review, guided by the methodology proposed by Donthu et al. (2021). Our literature search utilized both the Clarivate Web of Science and Scopus databases, complemented by the Biblioshiny software for literature selection and qualitative analysis. Employing a systematic approach, we meticulously collected, screened, and included data for analysis. Our search strategy involved using a combination of pertinent keywords related to impulse buying behavior, such as “Unplanned buying,” “Impulsive shopping,” and “Impulse purchase.” These keywords were applied within the TIT-ABS-KEY field of the Scopus search engine and the Topic field in the Web of Science database. The search strings utilized were (“impulse buy*” OR “impuls* purchase” OR “unplanned buy*”); AND (“Factors” OR “Determin*” OR “drivers” OR “influenc*”).Initially, our search yielded 944 articles, which were then exported in .CSV format for further analysis. To ensure the relevance of the included articles, we established stringent inclusion criteria. This involved meticulously examining the title and abstract of each paper to verify its alignment with the scope of our research. We specifically focused on articles written in English, while excluding short notes, editorial pieces, and non-research articles. After applying our inclusion criteria, 436 articles were excluded, leaving us with a pool of 508 high-quality articles for comprehensive analysis. These articles formed the basis for our subsequent analysis into the intellectual and social structures of impulse buying literature.

Data Analysis

To conduct descriptive and network analyses on the collected data (Figure-1), researchers employed the Biblioshiny web application within the R environment. This tool is renowned for its versatility in transforming data into meaningful visualizations and tables, making it a popular choice among researchers. Bashar et al. (2021) and Singh and Bashar (2021) have underscored the significance of Biblioshiny as a go-to method for researchers aiming to present their findings in clear and compelling ways.

Figure-1: Data Analysis



Source: Authors’ creation

Data Analysis

Descriptive Analysis

Data Overview

Table-1 offers a condensed yet informative snapshot of the various attributes associated with the bibliographic data gathered for the study. This comprehensive overview encapsulates key details such as publication titles, authors, publication years, sources, and other pertinent metadata. By presenting this data in a structured format, this table serves as a foundational reference point for further analysis and exploration of the research landscape surrounding the theme of impulse buying.

Table-1: Descriptive Overview of Data

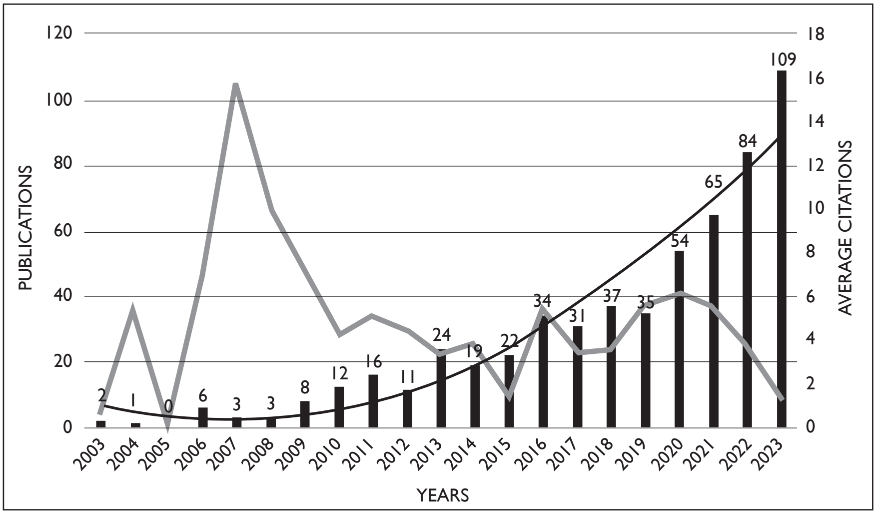
Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2003:2023
Sources (Journals, Books, etc)	244
Documents	508
Annual Growth Rate %	16.44
Document Average Age	5
Average citations per doc	23.66
References	8619
DOCUMENT CONTENTS	
Keywords Plus (ID)	1087
Author's Keywords (DE)	1471
AUTHORS	
Authors	1152
Authors of single-authored docs	46
AUTHORS COLLABORATION	
Single-authored docs	58
Co-Authors per Doc	2.9
International co-authorships %	12.38
DOCUMENT TYPES	
Article	403
Book Chapter	28
Conference paper	55
Review	22

Source: Biblioshiny

Annual growth in the volume of publications

The graph (Figure-2) depicts trends in publications and their average citations from 2003 to 2023. On the X-axis, years are marked, while the left Y-axis measures the number of publications, reaching a peak around 2004 before sharply declining. However, from 2015 onward, there is a gradual rise in publications. The grey line graph illustrates this pattern. Meanwhile, the right Y-axis displays average citations, with values steadily increasing over the years. Notably, there is a significant spike in average citations in 2023, indicated by the dark bars in the bar chart. Overall, the graph portrays a fluctuating yet upward trajectory in publications alongside a consistent rise in their average citations, offering insights into the evolving landscape of scholarly output and impact over time.

Figure-2: Trend of Publications and Citations on Impulse Buying from 2003-2023



Source: Authors' creation

To truly understand this trend, it is essential to thoroughly analyze the significant sources, authors, articles, prevalent themes, and influential factors that shape each document being considered. Through extensive evaluation of the forthcoming figures and tables, we aim to provide a comprehensive insight into the phenomenon.

Word Frequency Analysis

Table-2 provides an insightful breakdown of frequently used terms in relevant research studies, focusing on their occurrence as "Author keywords" within abstracts of at least 100 documents. Notably, the term "Impulse" emerges as the most prevalent, appearing a substantial 1567 times in the analyzed articles. Following "Impulse," other significant terms include "Buying," "online," "behavior," "factors," "hedonic," "retail," "time," "emotional," "mobile," "environment," and "promotion," each offering valuable insight into the thematic landscape of research on the topic. In essence, this frequency distribution offers a glimpse into the core themes and areas of interest within the extensive body of literature on impulse buying behavior, highlighting key trends and priorities shaping the field.

Table-2: Most Occurring Keywords

Keywords	Occurrences
Impulse	1567
Buying	1564
Online	751
Behavior	518
Factors	441
Hedonic	199
Retail	175
Time	145
Emotional	116
Mobile	115
Environment	101
Promotion	101

Source: Authors' creation

Word Cloud Analysis

The visualization presented in Figure-3 illustrates the significance of keywords in IBB research through a word cloud, where the size of each word corresponds to its frequency of occurrence in the document. In the realm of IBB, numerous established factors have been incorporated, such as "Materialism," "Sales Promotion," "Hedonic," "Customer Satisfaction," "Social Influence," and "Covid-19". Additionally, terms like "Online Impulse Buying," "Online Shopping," "Social Commerce," "E-Commerce," "social media," and "Website Quality" have garnered attention in research. In the ever-evolving landscape of consumer behavior amidst the digital age, grasping these factors holds pivotal importance for both businesses and researchers. As technology continues to reshape how individuals interact with products and services, delving into the intricacies of online impulse buying, social commerce dynamics, and website quality becomes imperative. This deeper understanding not only empowers businesses to tailor their strategies effectively but also equips researchers with valuable insights to navigate the complexities of modern consumerism.

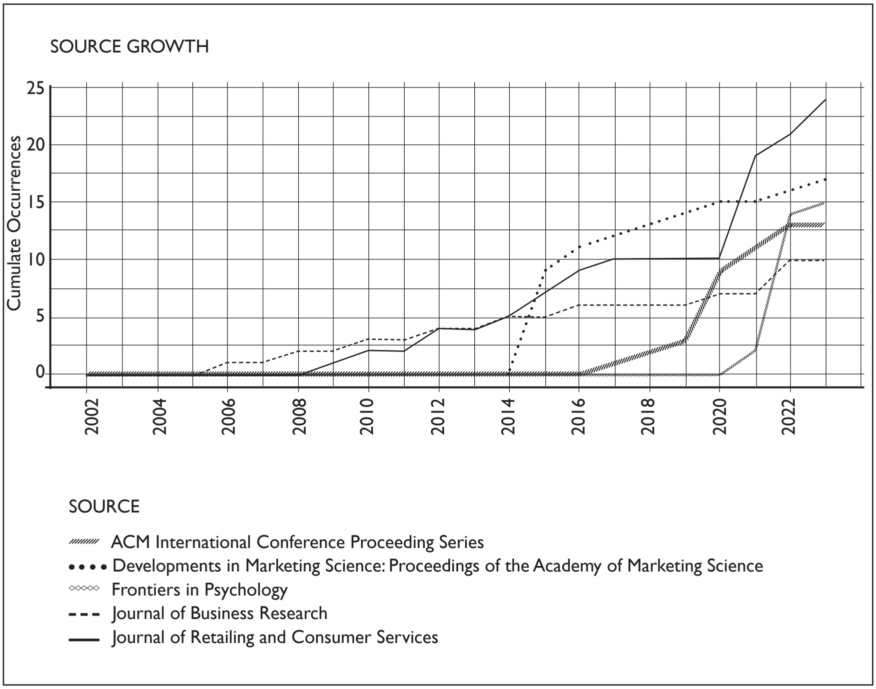
Figure-3: Word Cloud

Source: Biblioshiny

Top Growing sources

The analysis of source dynamics in supporting research in the field of IBB reveals a consistent and dynamic progression across five main sources (Figure-4). These findings highlight the active growth of journals such as "Journal of Retailing and Consumer Services," "Developments in Marketing Science: Proceedings of the Academy of Marketing Science," "Frontiers in Psychology," "ACM International Conference Proceeding Series," and "Journal of Business Research." These journals, currently indexed in reputable databases like the Social Science Citation Index (SSCI), underscore the dominance of key categories including "social psychology," "business & management," "consumer behavior and retailing," "computing innovation," and "marketing." In conclusion, this analysis emphasizes the significant contribution of these sources to the advancement of research in IBB, reflecting the evolving landscape and interdisciplinary nature of the field.

Figure-4: Top Growing Sources



Source: Biblioshiny

Top Cited Documents

Table-3 showcases the most frequently cited works, which are scholarly articles renowned for their significant professional influence and outstanding academic reputation, particularly in the realm of impulsive purchasing behavior.

Table-3: Most Cited Documents

Rank	Authors	Documents Title	Journal Title	TC
1	(Vohs & Faber, 2007)	"Spent Resources:Self-Regulatory Resource Availability Affects Impulse Buying"	*"Journal of Consumer Research"*	530
2	(Parboteeah et al., 2009)	"The Influence of Website Characteristics on a Consumer's Urge to Buy Impulsively"	*"Information Systems Research"*	416
3	(Xiang et al. 2016)	"Exploring Consumers' Impulse Buying Behavior on Social Commerce platform: The Role of Parasocial Interaction"	*"International Journal of Information Management"*	278
4	(Verhagen & Dolen, 2011)	"The influence of online store beliefs on consumer online impulse buying: A model and empirical application"	*"Information and Management"*	267
5	(Park et al., 2012)	"Apparel product attributes, web browsing, and e-impulse buying on shopping websites"	*"Journal of Business Research"*	223
6	(Chang et al., 2011)	"Application of the Stimulus-Organism-Response model to the retail environment: The role of hedonic motivation in impulse buying behavior"	*"The International Review of Retail, Distribution and Consumer Research"*	216
7	(Liu et al., 2013)	"Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions"	*"Decision Support Systems"*	212
8	(Chan et al., 2017)	"The state of online impulse-buying research: A literature analysis"	*"Information & Management"*	208
9	(Peck & Childers, 2006)	"If I touch it I have to have it: Individual and environmental influences on impulse purchasing"	*"Journal of Business Research"*	200
10	(Zheng et al., 2019)	"Understanding impulse buying in mobile commerce: An investigation into hedonic and utilitarian browsing"	*"International Journal of Information Management"*	192

Source: Authors' creation

Note: TC= Total Citations

Table-3 highlights Vohs & Faber's (2007) publication as the most cited work in the field, focusing on experiments that examined the impact of self-regulatory resource availability on resisting impulsive spending urges. Subsequent studies by Parboteeah et al. (2009) and Xiang et al. (2016) further contribute to our understanding by exploring triggers for impulsivity in online shopping environments and the impact of social relationships on IBB through social commerce platforms, respectively. Overall, these studies collectively highlight the multifaceted nature of IBB, spanning across various platforms and encompassing factors such as self-regulation, browsing behavior, personality traits, and social interactions. They provide valuable insights into the dynamics of consumer behavior in both offline and online retail settings, paving the way for further research and development in this evolving field.

Network Analysis

Within this study, network analysis unfolds across two distinct sections:
A. Intellectual Structure analysis dissects how an author's work influences the broader scientific community, employing Co-citation network analysis.

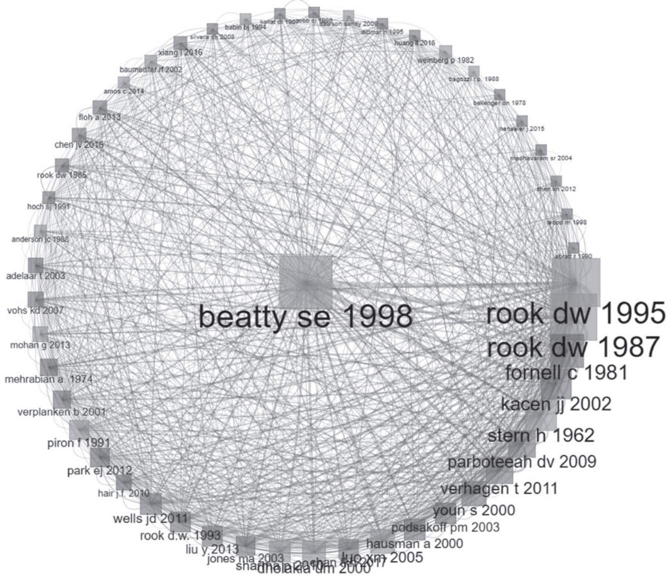
B. Delving into Social Structure, the study scrutinizes interactions among authors, institutions, and countries via Author Collaboration and Country Collaboration analyses.

Intellectual Structure: Co-citation Network Analysis

Drawing from the co-citation network, the study extracted the intellectual structure from the bibliographic dataset, leveraging instances where two papers are cited in a third document. This analysis unveils the foundational framework within a research domain, highlighting the frequency with which pairs of literature are referenced together in other documents. Figure-5 illustrates the co-citation network analysis, where robust connections between articles aid in clustering them. According to Lin & Himelboim (2019), an author co-citation network facilitates the identification of influential scholars' work within a particular knowledge domain with exceptional precision.

In this study, co-citation networks among influential cited publications and prevailing schools of thought within these networks were meticulously analyzed. The analysis gauges the likeness between documents, authors, and journals. Utilizing papers as the unit of analysis, with 50 nodes, and employing the Walktrap clustering algorithm, the diagram (Figure-5) unveils four distinct clusters of authors, each denoted by a different color, arranged in a star-shaped network layout.

Figure-5: Co-citation Network (by papers)



Source: Biblioshiny

Decoding Impulse Buying with Consumer Psychology, Personality Traits

The research in this cluster bridges the gap between individual predispositions and the irresistible pull of impulsive choices, facilitated by our inherent tendencies. A holistic understanding of the complex dynamics underlying individual culture, self-identitiy, personality traits, and impulsive tendencies was offered. Kollat and Willett's (1967) research focuses on discerning differences in unplanned purchasing behavior among consumers, whereas Youn & Faber (2000) explored the interrelation between impulse buying tendencies and personality traits, including the Big Five Traits. Verplanken and Herabadi (2001), with their magnifying glass, scrutinized the relationship between personality traits and compulsive buying behavior. Here, the mediating role of impulsive tendencies emerged – a bridge connecting our inner inclinations to the irresistible allure of products. Impulsive purchases often mirror an individual's self-identity, a concept which could be subject to gender influence (Dittmar et al., 1995). This notion gains further traction when considering the research conducted by Silvera et al. (2008), who evaluated the cross-cultural suitability of a gender identity scale within marketing strategies. Some viewpoints illustrated how people manage the equilibrium between impulsive inclinations and self-regulation strategies. Rook & Hoch (1985) delved into a psychological model unraveling consumer impulse buying episodes, while Vohs & Faber (2007) emphasized the importance and workings of the strength model of self-regulation within the broader context of human psychology. These perspectives interweave, offering a deeper comprehension of the intricate dynamics shaping consumer behavior and self-regulatory efforts. Researchers also demonstrates how both regional and individual cultural elements systematically influence impulsive buying tendencies (Kacen & Lee, 2002). The cluster integrates diverse perspectives and illuminates the multifaceted dynamics of consumer behavior, highlighting the interplay between personality traits, cultural influences, and self-regulatory mechanisms.

Complexities of E-Impulse Buying from Varied Perspectives

This cluster offers a comprehensive exploration into the multifaceted dynamics of online impulse purchasing behavior. Parboteeah et al. (2009) delved into the influence of website variations on online impulse purchases, focusing on website design. Building upon this, Verhagen & Dolen (2011) offered insights into the connection between consumers' beliefs about online stores and their tendency towards impulse buying. Wells et al. (2011) extended this exploration by emphasizing website quality as a pivotal environmental cue directly impacting the likelihood of impulsive purchases. Expanding the understanding of website cues, Liu et al. (2013) quantified the effects of product availability and visual appeal on consumer personality traits and their inclination towards online impulse buying. Together, these studies form a cohesive narrative, elucidating the intricate interplay between website elements, consumer beliefs, and personality traits in shaping online impulse purchasing behavior. Chen et al. (2016) undertook an online experiment to analyze how the quality of information in Facebook C2C advertisements affects impulsive buying urges. Complementing this research, Huang (2016) investigated methods to enhance impulsive buying tendencies, particularly within Social Networking Websites (SNSs), drawing insights from the SOR paradigm and social capital theory. This exploration aligns with Floh & Madlberger's (2013) extension of the S-O-R model, which evaluated how virtual atmospheric cues impact online impulse buying behavior and expenditure. Similarly, Xiang et al. (2016) introduced parasocial interaction theory to examine how social relationship factors influence impulse buying on social commerce platforms. The cluster provide a nuanced understanding of the mechanisms driving online impulse purchasing, considering the interplay between information quality, social dynamics, and environmental cues.

Multifaceted Dynamics and Influencing stimuli of Impulse buying behavior

This research cluster has embarked on an exploration of its multifaceted dynamics, probing its correlation with diverse stimuli and underlying drivers. Researchers such as Piron (1991), Rook (1987), and Stern (1962) laid the foundation for understanding the association between various stimuli and impulse purchasing tendencies. Amos et al. (2014) furthered this understanding through a meta-analysis, identifying common antecedents of impulse buying behavior, while Baumeister (2002) emphasized the role of self-control failure in impulsive purchasing. Weinberg & Gottwald (1982) delved into the emotional triggers behind impulse buying, whereas Rook & Fisher (1995) examined how consumers' normative evaluations influence the relationship between impulse buying traits and actual purchasing behavior. However, Luo (2005) provided insights into the impact of social influences on impulse buying. In a complementary approach, Beatty & Ferrell (1998) modelled the precursors to IBB, considering situational variables such as time and money availability, along with individual variables like shopping enjoyment and impulse buying tendency. Dawson & Kim (2009) further explored the internal and external factors shaping impulse buying, particularly in online shopping contexts. Valuable insights were provided into the complex interplay among impulsivity traits, situational variables, and constraining factors, shedding light on their impact on driving or inhibiting consumption impulses (Dholakia, 2000; Mohan et al., 2013). Collectively, these studies offer a holistic understanding of the complex phenomenon of impulse buying behavior and provide valuable insights into its determinants. The cluster findings contribute to a deeper understanding of the factors driving impulse buying behavior, offering insights that can inform both theoretical frameworks and practical strategies in consumer psychology and marketing.

Consumer Emotions, Impulse Buying and Theoretical & Analytical Insights

This cluster unravels the complexities of impulsive purchasing, while also examining analysis techniques and potential pitfalls through seminal articles and insightful books. From foundational works such as those by Fornell and Larcker (1981) and Mehrabian & Russell (1974) to contemporary studies by Adelaar et al. (2003), Madhavaram & Laverie (2004), and Park et al. (2012), this cluster contributes significantly to our understanding of the multifaceted nature of impulse purchasing in various contexts. Mehrabian & Russell (1974) laid the foundation by proposing a theory that connects environmental cues to impulse buying through primary emotional responses, initiating a trajectory of research into the emotional aspects of consumer behavior. Building upon this theoretical framework, subsequent studies have explored various facets of impulse buying in relation to emotions and environmental stimuli. Adelaar et al.

(2003) contribute to this field by investigating how different media formats influence emotions and impulse buying intentions, particularly for music CDs. Expanding the scope, Madhavaram & Laverie (2004) delve into impulse purchase behavior, incorporating variables like browsing behavior and mood states to understand online impulse buying. Their study extends these insights beyond traditional retail settings to the realm of Internet purchases. This research not only deepens our understanding of impulse buying but also underscores the importance of considering contextual factors in online consumer behavior. Building upon this foundation, Park et al. (2012) further enrich our comprehension by exploring the effects of hedonistic and utilitarian web browsing on e-impulse purchases on online apparel shopping platforms. Their study adds depth to our understanding of the intricate dynamics governing online consumer behavior, highlighting the interplay between consumer emotions, browsing behavior, and impulse purchases in the digital realm. Hair et al. (2010) complemented this by offering a user-friendly introduction to multivariate analysis, tailored for individuals lacking a statistical background. This accessible approach democratized the understanding of analytical techniques, facilitating their application in diverse research contexts. In a similar vein, Fornell and Larcker (1981) contributed to methodological advancements by developing and employing a testing framework centered on shared variance measures across structural, measurement, and overall models. Their work provided a robust methodological foundation for assessing the validity and reliability of research models. Podsakoff et al. (2003) extended this methodological discourse by delving into the influence of method biases on research outcomes, highlighting the importance of rigorously addressing potential biases to ensure the validity of research findings. In conclusion, Cluster 4 offers a comprehensive exploration of the intricate relationship between consumers' emotions, mood states, and Impulse Buying Behavior (IBB), complemented by an examination of analysis techniques and potential errors in their application.

As mentioned before, cluster 1 in red nodes focused on decoding impulse buying with consumer psychology, personality traits. Whereas, articles in cluster 2 in blue nodes are relevant to the complexities of e-impulse buying from varied perspectives. On the other hand, cluster 3 in green nodes also shows a reasonable relevancy of the articles notably on the multifaceted dynamics and influencing stimuli of Impulse buying behavior. Findings of cluster 4 in purple nodes suggest a close focus of articles on the consumer emotions, theoretical and analytical insights in association with impulse buying. Co-citation analysis provides an alternative to rigid boundaries in scientific assessment. These themes would assist in identifying research groups by recognizing collaborations and shared interests among scholars and understanding scholarly landscapes through these co-citation patterns.

Social Structure Analysis

Within this research domain, the social structure is visualized through collaboration networks among authors, institutions, and countries. These networks are forged from joint publications, elucidating the depth of collaboration among authors or author groups across diverse institutions.

Figure-6: Collaboration Network of Authors

Source: Biblioshiny

To construct the authors' collaboration network, parameters were meticulously selected: 50 nodes, symbolizing individual authors; a minimum of 2 edges denoting co-authorship relationships; an "Automatic network layout"; application of the "Walktrap Clustering algorithm"; and "association normalization" to refine peak similarities by their association strength.

Social Structure Analysis

- Author Collaboration Network
- Country Collaboration Map

Authors' Collaboration Network Analysis

The analysis of Authors' Collaboration Networks (Figure-6) assists in identifying the foremost authors and their collaborative efforts within distinct research streams pertaining to impulse buying. In exploring the intricate landscape of impulse buying behavior (IBB), scholars have unveiled a complex array of topics spanning multiple clusters. These clusters serve as a guide to deciphering the intricate nature of impulse buying behavior, providing valuable insights into the numerous factors shaping consumer behavior across diverse contexts.

Table-4: Clusters Based on Authors' Collaboration Analysis

Cluster Colour	Number of Articles in the Cluster	Theme Followed in the Articles of the Cluster
1. Red cluster	7 Articles	Consumer post-purchase behaviour after impulse shopping in terms of Gratification, Dissonance & Return Intention, Repeat buying & Consumer loyalty
2. Blue cluster	9 Articles	Impulse buying in emerging retail platforms i.e. Social Commerce, Live streaming commerce and Role of gamification and endorsement by celebrities and influencers in promoting IBB tendency in consumers
3. Brown cluster	5 Articles	Role of Self-regulation and Variety seeking in stimulation of IBB
4. Purple cluster	3 Articles	IBT in consumers of emerging markets i.e., India
5. Pink cluster	4 Articles	Influence of personality traits, behavioural factors and Promotional tactics on IB Tendency of buyers
6. Orange cluster	3 Articles	Impulse buying in Facebook Commerce
7. Lime Green cluster	4 Articles	Consumers' IB Decision in association with Individualist and Collectivist Culture, Environmental and Personality Characteristics
8. Grey cluster	2 Articles	Promoting IBB through CSR and green practices
9. Teal Green cluster	4 Articles	Online impulsive shopping behaviour of Chinese consumers

Source: Authors' creation

Across a spectrum of research endeavors, authors within these clusters (Table-4) have traversed diverse terrains, shedding light on nuanced facets of consumer behavior in contemporary markets. The authors within these clusters have delved into myriad of themes such as Consumer Post-Purchase Behavior, Impulse Buying on emerging retail platforms like Social Commerce (e.g., Facebook Commerce), and the online impulsive shopping tendencies of Chinese consumers. Their investigations encompassed a range of constructs including Individualist and Collectivist Culture, Gratification, Dissonance & Return Intention (Chen et al., 2020), Repeat Buying (Chen et al., 2020), the Role of Gamification (Zhang et al., 2021), as well as the influence of celebrity and influencer endorsements (Chen et al., 2021; Li et al., 2022). Additionally, they scrutinized the Impact of CSR and green practices in fostering and encouraging impulse buying behaviors among shoppers (Hayat et al., 2020; Hayat et al., 2022). Through meticulous inquiry and empirical analysis, these studies contribute to a richer understanding of the intricate mechanisms driving consumer choices and behaviors in the dynamic landscape of modern commerce.

Global Production Analysis

The distribution of publications on impulse buying behavior (IBB) globally, as depicted in Table-5, highlights China's considerable interest in this research area with 194 publications, followed by the United States of America with 113 publications and India with 85 publications.

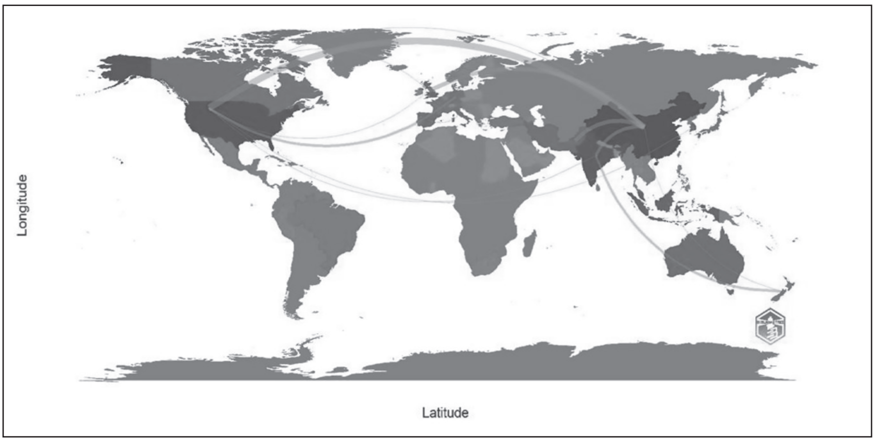
Table-5: Top Countries' Scientific Production on the theme of Impulse Buying

Region	Frequency	Region	Frequency
China	194	UK	22
USA	113	Spain	17
India	85	South Korea	15
Malaysia	40	Australia	14
Indonesia	27	Pakistan	12

Source: Authors' creation

China distinctly exhibits a heightened interest in the realm of impulsive shopping compared to the rest of the world. Moreover, the significant disparity observed in the number of publications between these three nations (China, USA, India) and the rest of the world underscores their prominence in the field.

Figure-7: Country Collaboration Map



Source: Biblioshiny

Country Collaboration Analysis

The examination of the global network structure, detailed in Table-6 and Figure-7, reveals a noticeable trend towards heightened cross-continental collaborative relationships in research concerning IBB. Particularly striking is the increasing frequency of collaborations between China and sixteen other nations, including the USA, Pakistan, UK, India, Australia, Canada, Finland, France, Ghana, Malaysia, New Zealand, Romania, Saudi Arabia, Singapore, Spain, and Vietnam. The USA emerges as the second most active collaborator, forming research partnerships with countries such as China, Germany, India, Korea, UK, Australia, Austria, Canada, France, Malaysia, Mexico, Netherlands, Pakistan, Portugal, Qatar, Spain, Switzerland, and Vietnam. India and the UK closely follow as the third and fourth top collaborators, with a substantial portion of their collaborations also involving China. Interestingly, Canada, Indonesia, Korea, and Norway emerge as the least collaborative countries in this network analysis. Overall, these findings underscore the increasingly globalized nature of research collaborations in the realm of IBB, with China playing a pivotal role in fostering partnerships across continents.

Table-6: Country Collaboration Network

From	To (Countries with Collaboration)	Frequency
China	USA(11), Pakistan (5), United Kingdom (5), India (4), Australia (1), Canada (2), Finland (1), France (1), Ghana (1), Malaysia (1), New Zealand (2), Romania (1), Saudi Arabia (1), Singapore (1), Spain (1),Vietnam (1)	39
USA	China (11), Germany (3), India (2), Korea (2), United Kingdom (2),Australia (1),Austria (1), Canada (1), France (1), Malaysia (1), Mexico (1), Netherlands (1), Pakistan (1), Portugal (1), Qatar (1), Spain (1), Switzerland (1),Vietnam (1)	33
India	China (4), New Zealand (3), USA (2),Australia (1), France (1), Germany (1), Ireland (1), Pakistan (1), Qatar (1), United Kingdom (1),	16
United Kingdom	China (5), Canada (2), USA (2), Denmark (1), India (1), Indonesia (1), Netherlands (1), Norway (1), Qatar (1)	15
Germany	USA(3),Australia (1),Austria (1), Brazil (1), India (1), Switzerland (1)	8
Australia	China (1), Germany (1), India (1), Japan (1), New Zealand (1), USA (1)	6
Spain	Italy (2), China (1), Netherlands (1), USA (1),	5
Pakistan	India (1), Saudi Arabia (1), USA (1),Vietnam (1)	4
Vietnam	China (1), Norway (1), Pakistan (1), USA (1)	4
Malaysia	Poland (1), Singapore (1), Sudan (1)	3
Canada	Korea (1), Iran (1)	2
Indonesia	Netherlands (1), United Kingdom (1)	2
Korea	Austria (1), Canada (1)	2
Norway	Denmark (1),Vietnam (1)	2

Source: Authors' creation

Conclusion

Initiating a thorough examination of impulse buying behavior literature spanning two decades, this study delves into the intricate facets and emerging trends shaping consumer actions and preferences. This study was conducted to provide a comprehensive review of existing literature on impulse buying behavior spanning from 2003 to 2023. It offers a bibliometric overview of prevalent trends concerning impulse buying and the factors driving it. The Annual Trend Analysis reveals a consistent increase in research on impulse purchases over the specified timeframe, with a significant surge observed in articles related to impulse buying from 2020 to 2023. Notably, the year 2007 stood out with the highest annual mean citation count, led by the seminal work of Vohs & Faber (2007). Employing science mapping techniques, the authors mapped the conceptual and social structures of impulse buying research, shedding light on emerging trends and focal points. Journal dynamics analysis underscores the growing significance of journals like the Journal of Retailing and Consumer Services in advancing research on impulse buying. Word analysis highlights key terms such as "Impulse," "buying," "internet," "behavior," and "factors," indicating a shift towards internet-based retailers in impulse buying research. Co-citation analysis delineates the intellectual structure of the research domain, revealing four distinct clusters addressing various aspects of consumer psychology, e-impulse buying complexities, influencing stimuli, consumer emotions, and theoretical insights. Moreover, Author Collaboration Network Analysis showcases diverse research themes explored by authors, including consumer post-purchase behavior, impulse buying in emerging retail platforms, and online impulsive shopping behavior in Chinese consumers. Finally, the global production distribution of publications underscores China's significant interest in impulse buying research, followed by the USA and India. Furthermore, the global network structure analysis highlights increasing cross-continental collaborations in impulse buying research, with China, USA, India, and the United Kingdom emerging as prominent collaborating nations. In conclusion, this comprehensive study not only illuminates the evolving landscape of impulse buying behavior research but also underscores the increasing global collaboration and shifting focus towards internet-based retail platforms in understanding consumer behavior dynamics.

Limitations

Despite its valuable insights, this research has limitations worth noting. By focusing solely on English-language articles, it may have missed out on important contributions from non-English literature. Although Scopus and Web of Science databases are extensive, they do not cover every publication in the field, which is another constraint. Moreover, relying exclusively on Scopus and Web of Science indexed papers further restricts the scope of the study. Nonetheless, despite these limitations, we anticipate that this review will encourage further exploration of the crucial topic of impulse buying outcomes in future research endeavors.

References

Adelaar, T., Chang, S., Lancendorfer, K., Lee B. & Morimoto M. (2003). Effects of media formats on emotions and impulse buying intent. *Journal of Information Technology, 18*(4), 247-266. https://doi.org/10.1080/0268396032000150799.

Bashar, A., Singh, S., & Pathak, V. K. (2021). A bibliometric review of online impulse buying behaviour. *International Journal of Electronic Business*, *17*(2), 162-183. https://doi.org/10.1504/ijeb.2021.10042816

Baumeister, R. F. (2002). Yielding to temptation: Self-control failure, impulsive purchasing, and consumer behavior. *Journal of Consumer Research, 28*(4), 670-676. https://doi.org/10.1086/338209

Beatty, S. E., & Ferrell, E. M. (1998). Impulse buying: Modeling its precursors. *Journal of Retailing*, *74*(2), 161-167. https://doi.org/10.1016/s0022-4359(98)90009-4

Chan, T. K., Cheung, C. M., & Lee, Z. W. (2017). The state of online impulse-buying research: A literature analysis. *Information & Management*, *54*(2), 204-217. https://doi.org/10.1016/j.im.2016.06.001

Chang, H. J., Eckman, M., & Yan, R. N. (2011). Application of the Stimulus-Organism-Response model to the retail environment: The role of hedonic motivation in impulse buying behavior. *The International review of retail, distribution and consumer research*, *21*(3), 233-249.

Chen, J. V., Su, B. C., & Widjaja, A. E. (2016). Facebook C2C social commerce: A study of online impulse buying. *Decision Support Systems*, *83*, 57-69. https://doi.org/10.1016/j.dss.2015.12.008

Chen, M., Xie, Z., Zhang, J., & Li, Y. (2021). Internet Celebrities' Impact on Luxury Fashion Impulse Buying. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(6), 2470-2489. https://doi.org/10.3390/jtaer16060136

Chen, W. K., Chen, C. W., & Lin, Y. C. (2020). Understanding the influence of impulse buying toward consumers' post-purchase dissonance and return intention: an empirical investigation of apparel websites. *Journal of Ambient Intelligence and Humanized Computing*. 1-14. https://doi.org/10.1007/s12652-020-02333-z

Dawson, S. & Kim, M. (2009). External and internal trigger cues of impulse buying online, *Direct Marketing: An International Journal*, *3*(1), 20-34. https://doi.org/10.1108/17505930910945714

Dholakia, U. M. (2000). Temptation and resistance: An integrated model of consumption impulse formation and enactment. *Psychology & Marketing*, *17*(11), 955-982. https://doi.org/10.1002/1520-6793(200011)

Ding, Y., DeSarbo, W., Hanssens, D., Jedidi, K., Lynch, J., and Lehmann, D. (2020). The past, present, and future of measurements and methods in marketing analysis. *Marketing Letters*, *31,* 175-186. https://doi: 10.1007/s11002-020-09527-7

Dittmar, H., Beattie, J., & Friese, S. (1995). Gender identity and material symbols: Objects and decision considerations in impulse purchases. *Journal of Economic Psychology*, *16*(3), 491-511. https://doi.org/10.1016/0167-4870(95)00023-h

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

Floh, A., &Madlberger, M. (2013). The role of atmospheric cues in online impulse-buying behavior. *Electronic Commerce Research and Applications*, *12*(6), 425-439. https://doi.org/10.1016/j.elerap.2013.06.001

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104.

Hair, J. F., Black, W.C., Babin, B. J. and Anderson, R. E. (2010). Multivariate Data Analysis. 7th Edition, *Pearson,* New York, 1-761.

Hashmi, H. B. A., Shu, C., & Haider, S. W. (2020). Moderating effect of hedonism on store environment-impulse buying nexus. *International Journal of Retail & Distribution Management*, *48*(5), 465-483. https://doi.org/10.1108/ijrdm-09-2019-0312

Hayat, K., Jianjun, Z., & Ali, S. (2022). Reinforcing purchase behaviors through CSR and ethical practices. *Marketing Intelligence & Planning*, *40*(2), 256-272. https://doi.org/10.1108/mip-08-2021-0268

Huang, L. T. (2016). Flow and social capital theory in online impulse buying. *Journal of Business Research*, *69*(6), 2277-2283. https://doi.org/10.1016/j.jbusres.2015.12.042

Iyer, G. R., Blut, M., Xiao, S. H., & Grewal, D. (2020). Impulse buying: A meta-analytic review. *Journal of the academy of marketing science, 48,* 384-404. doi.org/10.1007/s11747-019-00670-w

Joo Park, E., Young Kim, E., & Cardona Forney, J. (2006). A structural model of fashion-oriented impulse buying behavior. *Journal of Fashion Marketing and Management: An International Journal*, *10*(4), 433-446. https://doi.org/10.1108/13612020610701965

Kacen, J. J., & Lee, J. A. (2002). The Influence of Culture on Consumer Impulsive Buying Behavior. *Journal of Consumer Psychology*, *12*(2), 163-176. https://doi.org/10.1207/153276602760078686

Kim, A. J., & Johnson, K. K. (2016). Power of consumers using social media: Examining the influences of brand-related user-generated content on Facebook. *Computers in human behavior*, *58*, 98-108. https://doi.org/10.1016/j.chb.2015.12.047

Kollat, D. T., & Willett, R. P. (1967). Customer Impulse Purchasing Behavior. *Journal of Marketing Research*, *4*(1), 21. https://doi.org/10.2307/3150160

Li, L., Kang, K., Zhao, A., & Feng, Y. (2022). The impact of social presence and facilitation factors on online consumers' impulse buying in live shopping – celebrity endorsement as a moderating factor. *Information Technology & People*, *36*(6), 2611-2631. https://doi.org/10.1108/itp-03-2021-0203

Lin, J. S., Himelboim, I.(2019). Political Brand Communities as Social Network Clusters: Winning and Trailing Candidates in the GOP 2016 Primary Elections. *Journal of Political Marketing, 18*(1-2), 119-147. https://doi.org/10.1080/15377857.2018.1478661.

Liu, Y., Li, H., & Hu, F. (2013). Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions. *Decision Support Systems*, *55*(3), 829-837. https://doi.org/10.1016/j.dss.2013.04.001

Luo, X. (2005). How does shopping with others influence impulsive purchasing. *Journal of Consumer Psychology, 15*(4)*,* 288-294. http://dx.doi.org/10.1207/s15327663jcp1504_3

Madhavaram, S. R., &Laverie, D. A. (2004). Exploring Impulse Purchasing on the Internet. *Advances in Consumer Research*, *31, 59-66.*

Mandolfo, M., & Lamberti, L. (2021). Past, present, and future of impulse buying research methods: A systematic literature review. *Frontiers in Psychology, 12*(2), 1–11. https://doi.org/10.3389/fpsyg.2021. 687404

Mattila, A. S., & Wirtz, J. (2008). The role of store environmental stimulation and social factors on impulse purchasing. *Journal of services marketing*, *22*(7), 562-567.

Mehrabian, A. and J. Russell (1974). An Approach to Environmental Psychology. *The MIT Press,* Cambridge, Massachusetts*,* 1-266.

Mohan, G., Sivakumaran, B., & Sharma, P. (2013). Impact of store environment on impulse buying behavior. *European Journal of Marketing*, *47*(10), 1711–1732. https://doi.org/10.1108/EJM-03-2011-0110

Obukhovich, S., Sipilä, J., & Tarkiainen, A. (2023). Post-purchase effects of impulse buying: A review and research agenda. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.2287

Parboteeah, D. V., Valacich, J. S., & Wells, J. D. (2009). The influence of website characteristics on a consumer's urge to buy impulsively. *Information systems research*, *20*(1), 60-78. https://doi.org/10.1287/isre.1070.0157

Park, E. J., Kim, E. Y., Funches, V. M., & Foxx, W. (2012). Apparel product attributes, web browsing, and e-impulse buying on shopping websites. *Journal of business research*, *65*(11), 1583-1589. https://doi.org/10.1016/j.jbusres.2011.02.043

Peck, J., & Childers, T. L. (2006). If I touch it I have to have it: Individual and environmental influences on impulse purchasing. *Journal of business research*, *59*(6), 765-769. https://psycnet.apa.org/doi/10.1016/j.jbusres.2006.01.014

Piron F. (1991). Defining Impulse Purchasing. Advances in Consumer Research, 18, 509-514.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y. and 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), 879-903.

Redine, A., Deshpande, S., Jebarajakirthy, C., & Surachartkumtonkun, J. (2022). Impulse buying: A systematic literature review and future research directions. *International Journal of Consumer Studies, 47*(1), 3-41. https://doi.org/10.1111/ijcs.12862

Rodrigues, R. I., Lopes, P. and Varela M. (2021). Factors Affecting Impulse Buying Behavior of Consumers. *Frontiers in Psychology, 12*(1), 1-3. https://doi.org/10.2501/JAR-2018-031

Rook, D. W. (1987). The Buying Impulse. *Journal of Consumer Research*, *14* (2), 189-199. https://doi.org/10.1086/209105

Rook, D. W., & Fisher, R. J. (1995). Normative influences on impulsive buying behavior. Journal of Consumer Research, 22(3), 305-313. https://doi.org/10.1086/209452

Rook, D. W., & Hoch, S. J. (1985). Consuming impulses. *Advances in consumer research*, *12*(1), 23-27.

Santini, F.D.O., Ladeira, W.J., Vieira, V.A., Araujo, C.F. and Sampaio, C.H. (2019). Antecedents and consequences of impulse buying: A meta-analytic study. *RAUSP Management Journal, 54*(2), 178-204. https://doi.org/10.1108/RAUSP-07-2018-0037

Sharma, P., Sivakumaran, B., & Marshall, R. (2010). Impulse buying and variety seeking: A trait-correlates perspective. *Journal of Business Research*, *63*(3), 276-283. https://doi.org/10.1016/j.jbusres.2009.03.013

Silvera, D. H., Lavack, A. M., & Kropp, F. (2008). Impulse buying: the role of affect, social influence, and subjective wellbeing. *Journal of Consumer Marketing*, *25*(1), 23-33. https://doi.org/10.1108/07363760810845381

Singh, S., & Bashar, A. (2021). A bibliometric review on the development in e-tourism research. *International Hospitality Review*, *37*(1), 71-93. https://doi.org/10.1108/ihr-03-2021-0015

Stern, H. (1962). The Significance of Impulse buying Today. *Journal of Marketing*, *83*(1), 72-72. https://doi.org/10.1111/j.1600-0390.2012.00570.x

Strack, F., & Deutsch, R. (2006). Reflective and impulsive determinants of consumer behavior. *Journal of Consumer Psychology, 16*(3), 205-216.

Varadarajan, R. (2020). Customer information resources advantage, marketing strategy and business performance: A market resources based view. *Industrial Marketing Management, 89,* 89-97. https://doi.org/10.1016/j.indmarman.2020.03.003

Verhagen, T., & van Dolen, W. (2011). The influence of online store beliefs on consumer online impulse buying: A model and empirical application. *Information & Management*, *48*(8), 320-327. https://doi.org/10.1016/j.im.2011.08.001

Verplanken, B., &Herabadi, A. (2001). Individual differences in impulse buying tendency: feeling and no thinking. *European Journal of Personality*, *15*(1), 71-83. https://doi.org/10.1002/per.423

Vohs, K., & Faber, R. (2007). Spent Resources: Self-Regulatory Resource Availability Affects Impulse Buying. *Journal of Consumer Research*, *33*(4), 537-547. https://doi.org/10.1086/510228

Weinberg, P., & Gottwald, W. (1982). Impulsive consumer buying as a result of emotions. *Journal of Business Research, 10*(1), 43-57.

Wells, J., Parboteeah, V., & Valacich, J. (2011). Online Impulse Buying: Understanding the Interplay between Consumer Impulsiveness and Website Quality. *Journal of the Association for Information Systems*, *12*(1), 32-56. https://doi.org/10.17705/1jais.00254

Xiang, L., Zheng, X., Lee, M. K., & Zhao, D. (2016). Exploring consumers' impulse buying behavior on social commerce platform: The role of parasocial interaction. *International Journal of Information Management*, *36*(3), 333-347. https://doi.org/10.1016/j.ijinfomgt.2015.11.002

Xiao, S. H., & Nicholson, M. (2013). A multidisciplinary cognitive behavioural framework of impulse buying: A systematic review of the literature. *International Journal of Management Reviews, 15*(3), 333-356. https://doi.org/10.1111/j.1468-2370.2012. 00345.x

Youn, S., & Faber, R. J. (2000). Impulse buying: Its relation to personality traits and cues. *Advances in consumer research*, *27*(1).

Zhang, L., Shao, Z., Li, X., & Feng, Y. (2021). Gamification and online impulse buying: The moderating effect of gender and age. *International Journal of Information Management*, *61*, 102267. https://doi.org/10.1016/j.ijinfomgt.2020.102267

Zheng, X., Men, J., Yang, F., & Gong, X. (2019). Understanding impulse buying in mobile commerce: An investigation into hedonic and utilitarian browsing. *International Journal of Information Management*, *48*, 151-160. https://doi.org/10.1016/j.ijinfomgt.2019.02.010

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

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TFP Growth in Manufacturing Sector: Evidence from India and China

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Abstract

Using the growth decomposition method used present study estimated the contribution from input growth, scale effect, technical progress and technical efficiency towards output growth. Analysing TFPG growth it has been found that technical progress has played major role in both economies and both lacking at efficiency front with India being behind China. China's manufacturing has shown higher TFPG and efficiency in H-T industries whereas L-T industries showed inefficiency effects. While, Indian manufacturing seemed to be backed up by high technical progress in M-L-T industries. In Indian economy technical progress failed to surpass the contribution of input growth towards output growth whereas China's manufacturing showed significantly more contribution by TFPG in output growth of the manufacturing sector. Therefore, the challenge for India lies in strengthening its L-T and labour intensive base first so as to take the advantage of low labour cost and its vast labour pool. In India L-T industries have shown improved efficiency but this has been accompanied by low technical progress. India needs a firm base in low end products in the value chain so as to embark on the path of high end product manufacturing with high rate of technical progress and higher technical efficiency

Keywords: China, India, Manufacturing, Technical Efficiency, TFPG, Technical Progress

Introduction

The Manufacturing sector has been regarded as the engine of economic growth. A sparkling example of manufacturing led economic growth model has been presented by China in last few decades. China's impressive performance in the manufacturing sector has stunned the world even as it

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increased its cheaply produced exports across the world. Indian economy on the other hand could not replicate the growth experience of the developed economies who followed traditional growth path. The manufacturing sector of India still contributes very little towards the national GDP, compared with the other developed and developing economies especially China. In the present era of continuous technological advancement all over the world efficiency improvement is one of the key to remain competitive. The “knowledge gap” can only be bridged by improving productivity and being efficient. While comparing manufacturing sector of India and China we need to observe that whether the superior performance of Chinese economy has been input driven or relies upon technical progress and efficiency. Cross country comparisons are always fruitful and help to guide further growth trajectories. India and China both can learn a lot from each other. The major area of focus of the present study has been the comparison of productivity and efficiency of manufacturing industry of both economies and to find out the factors which led to the better performance of Chinese manufacturing over India.

Review of Literature

To reiterate, successful industrialization requires structural shift within the manufacturing sector. Various scholars have classified the manufacturing sector into different ‘subgroups’ to find out the structural shift from one subgroup to another, thus defining the ‘pattern of industrialization’. Hoffman (1956) divided the manufacturing industries into ‘usebased’ sectors wherein ‘consumer goods’ sector developed first. Chenery and Taylor (1968) divide them into three subgroups, that is, early, middle and late industries. Further, Syrquin and Chenery (1989) classified the manufacturing sector into two subsectors – light and heavy industries. But apart from the varied terminology used in the respective studies, it is found that in the initial stages low skilled and highly labour-intensive industries like textiles, food products, leather and furniture comes up; followed by relatively highly skilled and technology intensive industries like metal, vehicles etc, moving up to engineering and chemical industries at the higher level in technological ladder.

On the theoretical front, going beyond the neo-classical view, in which technological progress is exogenous, the endogenous growth theories which evolved in the late 1980s regarded investment in research and development (R&D) as an important factor for growth, which makes it imperative to re-define the terminology used for the classification of industries within the manufacturing sectors by taking R&D content into its preview. Thus, based on the technological contents, the low technology intensive industries should be followed by the high technology intensive industries defining the structural shift which determines the ‘pattern of industrial growth’. That is, in the initial stages the low technology and unskilled labour intensive industries dominates and subsequently the relatively high technology intensive industries should take the realm. The dominance of a particular subsector can be understood as its relative high proportion of 'value added' and /or 'employment'. Moving up the technological ladder from the initial stages to the subsequent ones' entails sustainability as it corresponds to relatively higher income elasticity of demand (Lall, 2001) along with the higher labour productivity and higher labour productivity growth (Edquist et al, 2001).

Thus, the interdependence of both the demand and supply factors works in tandem to climb the technology ladder. The process can be explained as under:

To begin with, the higher labour productivity due to the inclusion of technology might increase income and consumption. Then it would simultaneously produce the income effect on demand (ibid). This change in the demand components exerts the pressure on the supply side which again changes the technological contents. This further changes the trade pattern depending upon the comparative advantage of the countries concerned. But apart from the economic causality, the country's initial structure, natural resource endowments, and development policies (Chenery and Syrquin, 1986) plays an important role in determining the structural transformation. The transformation can take the pattern of modern industrialization, dubbed as '*the flying geese paradigm*', in which as the new and more dynamic industries emerge, the traditional ones are phased out or may even be left entirely to countries at the earlier stages of development (Akyuz, 2009). Recently, Imbs and Wacziarg (2000) found a unique pattern of industrialization, regarded as the *'U-shaped pattern'* of specialization-diversification- specialization, wherein the early stages of industrialization are characterized by sectoral specialization in exploiting endowments of natural resources and unskilled labour. This is followed by diversification into a wide spectrum of more technologically advanced activities, but there exists a point, although late in the development process wherein they start to specialize again, this time in technologically advanced industries.

Economic theories associate high-technology intensive sector with the economic growth of a nation. As an economy grows, a shift from a natural resource based and low technology intensive manufacturing to high technology intensive manufacturing is bound to happen. Global value added of high-technology manufacturing was $1.5 trillion in 2012, making up 14% of the manufacturing sector. While, China, with a 23.92% global share, was the second largest producer of hi-tech products, India with a 0.93% global share was a distant laggard. The National Manufacturing Policy, 2011 and the 12th Five Year Plan (2012-17) acknowledge the urgency to attain more 'breadth' and 'depth' in manufacturing, implying not only improvement in the production of similar goods but also diversifying into more complex products and moving up the manufacturing value chain (Kathuria et.al, 2014).

Objectives

- To examine and compare the growth trends in organised manufacturing sector's output and employment in both India and China.
- To examine and compare the labour productivity, technical efficiency and total factor productivity of manufacturing sector in both countries

In the present section, in order to analyse the technological complexion of the manufacturing sector, industries have been re-classified according to the technology based classification provided by the Organisation for Economic Cooperation and Development (OECD) (2007), into four categories, that is, High Technology industries (H-T), Medium-High Technology industries (M-H-T), Medium-Low Technology industries (M-L-T) and Low Technology (L-T).

Table-1 reveals that in Indian manufacturing H-T industry only constituted 4.4 percent of total GVA and 2.8 percent of total manufacturing employment in 1998-99 which change to a mere 3.2 percent contribution to GVA and employment share of H-T industry came slightly down to 2.3. The contribution of H-T manufacturing in Chinese manufacturing GVA has been 11.5 percent and 7.3 percent in employment in the year 2010-11 which increased to 12.5 percent of total GVA and 12.2 percent of total manufacturing employment in 2015-16. We can see that how minimal is the size of H-T manufacturing in India as compared to China.

Indian manufacturing GVA was dominated by M-H-T industry in 1998, and later in 2015-16, M-L-T industries took the lead in terms of manufacturing GVA. But employment side has been dominated by L-T industries during the whole period of analysis with a little decrease in employment contribution of L-T industries from 48 percent in 1998 to 45 percent in 2015-16. The share of L-T industries in total manufacturing GVA decreased from 28.7 percent in 1998-99 to 22.9 percent. So for the whole period major gainer in both GVA and employment has been M-L-T industries which showed a capital intensive nature with total increase of 12 percent in GVA contribution and 6.4 percent increase in employment contribution.

TFPG and its Components in Indian and Chinese Manufacturing

In the present era of continuous technological advancement all over the world efficiency improvement is one of the key to remain competitive. The "knowledge gap" can only be bridged by improving productivity and being efficient. While comparing manufacturing sector of India and China we need to observe that whether the superior performance of Chinese economy has been input driven or relies upon technical progress and efficiency. So in the present section, we will examine various components of output growth (input growth, scale efficiency, technical progress and technical efficiency change) of manufacturing sector in both economies and see whether Chinese manufacturing has shown more improvement in technical progress, technical efficiency level or depends upon input growth in comparison to Indian manufacturing over the period of time.

Data and Variables Used for Time Varying Stochastic Production Frontier Efficiency Model

Three-digit level data on manufacturing sector of both India and China has been used covering the time period of 1998-2015 for India and 1999-2015 for China[1]. The source of Indian data is ASI and the Chinese three-digit level data on manufacturing sector has been taken from CDO, compiled by China Data Centre of University of Michigan. CDO takes data from National Bureau of Statistics, China (NBS). The three-digit level data have been concorded for the various industrial classifications followed in both countries and have been made compatible with ISIC-revision 3. Finally, fifty-four, three-digit industries for India and fifty-two, three-digit level industries for China have been analysed.

Table-1: Technology Intensity of Indian and Chinese Manufacturing

India												
	Value Added						**Employment**					
	Share		**Growth Rates**				**Share**		**Growth Rates**			
	1998-1999	**2015-2016**	**1998-2005**	**2005-2010**	**2010-2015**	**1998-2015**	**1998-1999**	**2015-2016**	**1998-2005**	**2005-2010**	**2010-2015**	**1998-2015**
HT	4.4	3.2	2.2	11.7	11.0	8.6	2.8	2.3	-5.3	4.1	1.8	-0.2
MHT	40.1	35.0	-0.4	15.5	18.8	12.2	27.9	24.5	-5.9	3.8	4.3	2.9
MLT	27.1	39.1	3.1	18.4	14.8	15.2	21.8	27.2	-2.3	6.0	3.6	4.4
LT	28.7	22.9	4.3	14.8	11.8	10.0	48.0	45.8	0.2	6.3	2.1	3.2
All	**100**	**100**	**2.3**	**15.1**	**14.7**	**11.5**	**100**	**100**	**-3.3**	**4.2**	**4.1**	**2.6**

China												
	Value Added						**Employment**					
	Share		**Growth Rates**				**Share**		**Growth Rates**			
	1998-1999	**2015-2016**	**1998-2005**	**2005-2010**	**2010-2015**	**1999-2015**	**1999-1999**	**2015-2016**	**1999-2005**	**2005-2010**	**2010-2015**	**1999-2015**
HT	11.5	12.5	15.7	7.9	8.3	12.8	7.3	12.2	6.7	5.4	2.6	6.6
MHT	25.5	29.2	10.1	16.3	8.9	14.5	22.2	29.6	1.4	6.9	2.1	4.9
MLT	26.9	30.2	9.4	24.0	11.9	19.4	31.6	24.8	-2.7	6.1	1.0	3.1
LT	36.0	28.0	1.5	12.4	17.2	11.3	39.0	33.5	1.7	2.2	3.9	-1.0
All	**100.0**	**100.0**	**9.2**	**15.2**	**11.6**	**14.5**	**100.0**	**100.0**	**1.8**	**5.1**	**2.4**	**3.4**

Source: Prepared by author from ASI, Various Years and CDO, China dataset.

1 For China the accessible 3-digit level data started from the year 1999 only.

We have used the two-input production function where value added has been taken as a measure of output and capital and labour has been taken as two inputs. The three-digit industries have been further classified into four technology intensive industrial sub-groups (Appendix A3) based upon the classification provided by Organisation for Economic Cooperation and Development (OECD, 2007).

Empirical Model

The stochastic frontier model with panel data is:

$$\text{In } Y_{it} = \beta_0 + \beta_K \text{InK}_{it} + \beta_L \text{InL}_{it} + \beta_{KK} (\text{InK}_{it})^2 + \beta_{LL} (\text{InL}_{it})^2 + \beta_{KL} (\text{InK}_{it})(\text{InL}_{it}) + \beta_{Lt} (\text{InL}_{it})t + \beta_{Kt} (\text{InK}_{it})t + \beta_t t + \beta_{tt} t^2 + v_{it} - u_{it.} \quad ...(1)$$

where i=1, …N industries and t=1, …T; ln Y_{it} is the log of real industrial value added for i[th] industry at time t, ln K_{it} is the log of fixed capital stock, ln L_{it} is the log of number of employees. The random error v_{it} is symmetric and normally distributed with $v_{it} \sim N(0,\sigma_v^2)$. The technical inefficiency term u_{it} can either be time variant or time invariant (Lovell, 2000). In the case of time invariant technical inefficiency, $u_{it} = u_{i \sim} N^{+}(\mu, \sigma_u^2)$, where μ is the mode of the truncated half-normal distribution. In the case of time variant technical inefficiency, u_{it} can be expressed as a monotonic 'decay' function as $u_{it} = \eta_t u_{i,}$ where $\eta_t = \exp(-\eta(t - T)$, and η is an unknown scalar parameter for technical inefficiency. The u_{it} can either be increasing (if η< 0), decreasing (if η> 0) or remain constant (if η= 0) (Battese and Coelli, 1992). The minimum- mean-square-error predictor of the technical efficiency of the i[th] industry at time *t* is shown as (Battese and Coelli, 1988, 1992, 1995; Battese and Corra, 1977; Coelli, 1996; Kumbhakar and Lovell, 2000):

$$TE_{it} = E(\exp(-u_{it}) | \varepsilon_{it}) \quad ...(2)$$

Where $\varepsilon_{it} = v_{it} - u_{it}$

In the present study we have taken time varying efficiency model for all industries and all sub periods based on the results of our hypothesis testing.

Estimates of Stochastic Production Function for China

The maximum liklihood estimates of stochastic frontier production function in translog specification with time varying inefficiency for the sub-periods, 1998-2005, 2005-2010, 2010-2015 and period as a whole 1998-2015 are presented in Table-4 for India. The estimated coefficient of time varying technical inefficiency has been found mostly positive for all sub periods and all sub-groups of manufacturing sector except for a negative coefficient of high-technology industries for first two sub-periods and medium high tech showing negative coefficient of inefficiency decay in the initial phase. In the latter periods all industries showed significant improvement in efficiency in Indian manufacturing. The time varying technical (in)efficiency parameter has been found to be 0.023. It implies that level of technical efficiency in Indian manufacturing has during 1998-2015 has been increasing to the extent of 2.3 per cent. The estimates of time coefficient show significant technical progress in all sub-categories of Indian manufacturing during 1998-2015. The other two parameters γ and σ^2 are associated with the variance of the random variable V_{it} and U_{it}. Significance of parameters γ and σ^2 implies that the realised output differed from potential output significantly and the difference has been mainly due to the difference in the industry specific technical efficiency and not due to any random changes.

The coefficients of the translog production function cannot be directly interpreted economically, therefore in Table-2 presents the estimated values of the output elasticity with respect to the inputs of capital and labour. Returns to scale, input growth, adjusted scale effect, rate of technical progress and rate of change of technical efficiency have also been estimated. As shown in Table-2, labour has the greater output elasticity as compared to capital. For manufacturing as whole the output elasticities for labour and capital have been .699 and .419 during 1998 to 2015 respectively. Output elasticity of capital has been decreasing over the years which hints towards low productivity of capital in Indian manufacturing whereas output elasticity of labour has shown improvement. The estimates of these elasticities show similar trends for sub-groups of manufacturing sector considered here. Input growth has been highest in M-L-T sector followed by H-T industry. H-T industries showed lowest input growth due to low growth of labour input.

Now if we look at industry wise technical efficiency change in various sub-periods it becomes clear that in the initial phase all the industries witnessed negative technical efficiency change except H-T industries. It was during 2005-10 that most of the technical efficiency improvement happened in all industries with L-T industries followed by M-L-T industries taking the lead in technical efficiency improvement. H-T industries showed lowest technical efficiency improvement during 1998-2015.

Technical progress has failed to surpass input growth in Indian manufacturing during 1998-2015. Only during 2005-10 technical progress contributed more towards output growth of manufacturing sector than input growth. H-T industries have shown the lowest rate of technical progress and input growth contributed more towards output growth. H-T sector of Indian manufacturing seems to lack the dynamism which could only be attained by improving research and technical efficiency in this sector. M-H-T and M-L-T industries showed quite significant technical progress which contributed towards output growth in these industries. M-H-T industry showed highest technical progress during 1998-2015.

Estimates of Stochastic Production Function for China

The maximum likelihood estimates of stochastic frontier production function in translog specification with time varying inefficiency for the sub-

Table-2: Stochastic Frontier Production Function Estimates for Indian Manufacturing Industry and its Four Technological Sub- Categories (1998-2015)

Variable	Parameter	Manufacturing Total				High Technology Industries				Medium-High Tech				Medium-Low Tech				Low Tech			
		1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015
Constant	β_0	1.06	0.44	0.97	1.09***	1.32***	-0.49	0.28	0.9***	1.52***	0.49***	0.99	0.97***	3.27***	3.12***	3.09	3.18***	1.41***	0.63***	0.73	1.21***
		(1.36)	(0.43)	1.83	(2.86)	(5.39)	(-1.1)	(2.8)	(4.5)	(5.3)	(1.98)	2.9	(4.6)	(4.51)	(6.15)	5.1	(6.9)	(10.2)	(2.4)	4.7	(8.66)
Capital	β_K	0.59	0.43	0.48	0.50***	0.82***	0.33***	0.49	0.66***	0.61***	0.52***	0.61	0.69***	4.59***	4.35***	4.09	8.71	0.80***	0.72***	0.67	0.71***
		(0.83)	(0.59)	-0.71	(8.41)	(5.02)	(4.17)	(7.61)	(14.2)	(6.12)	(9.07)	12.3	(7.3)	(2.5)	(5.5)	(0.24)	(0.12)	(11.3)	(6.7)	11.2	(17.5)
Labour	β_L	0.5	0.71*	0.83	0.68***	0.78	0.81***	0.77	0.73***	0.42***	0.55***	0.45	0.38***	0.68***	0.77***	0.52	0.61***	0.39***	0.65***	0.55	0.43***
		(1.6)	(2.02)	1.61	(7.59)	(0.2)	(8.03)	6.14	(7.64)	(4.6)	(10.8)	7.7	(8.3)	(5.8)	(11.6)	9.7	(13.8)	(4.45)	(8.2)	10.1	(11.8)
K*K	β_{KK}		0.002	-0.2	-0.5***	5.34	-0.02	-3.96	4.9	2.84	4.8*	-4.69	-2.54	-0.72	0.73***	-0.72	0.25***	-2.19	0.3*	2.19***	0.07***
			(0.002)	-2.03	(-4.07)	(1.4)	(-0.2)	-0.8	(1.5)	(0.66)	(1.8)	(-0.6)	(-0.30)	(-1.01)	(4.17)	-3.4	(2.4)	(-0.46)	(1.76)	2.8	(-2.3)
L*L	β_{LL}		0.05***	0.04	0.0001	0.79***	0.96***	0.92	0.89***	0.96***	0.84***	0.6	0.97***	0.07	0.02***	0.04***	0.00	0.89***	0.06	0.06	-0.01
			(3.7)	1.8	(1.04)	(7.1)	(6.12)	9.01	(11.1)	(10.2)	(6.18)	7.8	(9.01)	(1.5)	(3.8)	4.4	(0.5)	(7.5)	(0.88)	4.03	(-0.2)
K*L	β_{KL}		0.04	0.01	0.02***	(2.4)	1.21	1.1	0.47*	0.71	0.84**	0.7	0.66	0.13**	0.48***	0.21	0.08***	-1.1	0.06***	-1.1	0.05***
			(0.14)	0.16	(2.65)	(1.30)	(0.18)	.99	(1.8)	(0.92)	(2.06)	1.8	(0.34)	(2.17)	(4.6)	5.3	(4.8)	(-0.8)	(2.71)	3.1	(1.86)
Time	β_T	0.03	0.5**	0.06*	0.4***	0.9	1.19	2.01	0.79*	0.85	0.92**	1.02	0.66	0.53**	0.24***	0.3***	0.8***	-1.4	0.07***	-2.7	-0.01***
		(0.27)	(3.14)	2.16	(2.76)	(2.41)	(0.97)	1.03	(3.8)	(0.92)	(3.16)	3.8	(1.14)	(3.27)	(4.11)	5.2	(4.1)	(-0.41)	(2.82)	-1.1	(-3.24)
T*K	β_{TK}	0.03	0.01	o.03	-0.06***	4.34	0.02	-3.96	6.6	1.8	-4.7*	-4.69	-4.54	-1.12	-0.33***	-0.56	0.26***	-3.89	-0.5*	-2.2	0.11***
		(0.03)	(0.002)	2.03	(-4.07)	(1.4)	(0.2)	-0.7	(3.7)	(-0.66)	(-1.8)	-0.6	(-0.30)	(-1.31)	(-5.07)	-3.8	(4.4)	(-0.66)	(-1.76)	-2.8	(14.1)
T*L	β_{TL}	-0.01	-0.05	-0.03	-0.01***	-0.04	-0.07	-0.07	-0.02*	-0.06	-0.04**	-0.04	-0.01	-0.04**	-0.01***	-0.1	-0.03***	0.08	-0.03***	0.08	0.01***
		(-1.07)	(-0.43)	-1.2	(-2.4)	(-1.1)	(-0.18)	-1.08	(-1.9)	(0.91)	(-1.99)	0.54	(-0.35)	(-2.23)	(-4.64)	-0.34	(-4.1)	(0.85)	(-3.7)	1.09	(8.14)
T*T	β_{TT}	-0.02	-0.05	-0.03	-0.01***	-0.04	-0.07	-0.07	-0.02*	-0.06	-0.04**	-0.04	-0.01	-0.04**	-0.01**	-0.1	-0.03	0.08	-0.03***	0.08	0.02
		(-0.04)	(-0.13)	-1.5	(-2.3)	(-1.4)	(-0.19)	-1.18	(-1.7)	(0.81)	(-1.79)	0.44	(-0.25)	(-2.14)	(-3.04)	-0.15	(-1.1)	(0.85)	(-3.7)	1.09	(-2.01)
σ^2		0.23***	0.19***	0.2	0.22***	0.37***	2.23	2.23	0.85*	0.73	0.27***	1.365	2.00	0.5***	0.25***	0.31	0.38***	0.53	0.14***	0.53***	1.08
		(9.47)	(7.4)	10.2	13.3	(3.36)	(0.19)	1.01	(1.83)	(0.85)	(2.5)	0.5	(0.35)	(9.5)	(7.8)	8.9	(11.9)	(0.94)	(11.6)	3..3	(6.78)
γ		0.06***	0.03***	0.05	0.001	0.65***	0.55***	0.82	0.79***	0.81***	0.77***	0.61*	0.87***	0.08	0.03***	0.05**	0.001	0.79***	0.07	0.13***	0.32
		(3.2)	(2.8)	1.03	(1.04)	(4.7)	(4.12)	7.41	(10.0)	(12.1)	(8.08)	(2.1)	(11.0)	(0.53)	(3.8)	3.1	(1.1)	(4.9)	(0.54)	4.13	(-3.91)
μ		2.04	1.07	0.99	1.09***	0.02***	1.07	2.03	1.9***	-0.76	2.49***	1.99	2.97***	3.28***	3.12***	3.09	3.17***	0.69***	3.63***	2.73	2.19
		(1.36)	(0.18)	1.76	(2.16)	(4.1)	(-1.1)	(2.8)	(4.5)	(19.1)	(1.91)	2.5	(4.4)	(3.81)	(5.05)	(3.1)	(7.8)	(7.5)	(2.1)	(3.6)	(-4.06)
η			0.03***	0.4	0.023		0.006***	0.62	0.32***		0.64***	0.61	0.47***	0.7	0.3***	0.45	0.01		0.04	0.02	3.61
			(2.7)	1.8	(1.04)		(6.42)	9.21	(13.0)		(9.68)	7.8	(14.0)	(0.91)	(7.8)	3.1	(0.5)		(0.88)	4.03	(-3.02)
LLF		-388.7	-404.1	-603.8	-830.4	-36.5	-55.0	-83.0	-111	-46.9	-39.8	-64.2	-106	-135.7	-107.7	-171	-270.2	-14.5	-107.4	-61	352.7
Nobs		216	324	216	702	28	42	28	91	60	90	60	195	48	72	48	156	80	120	80	260

Source: Prepared by author using ASI, India. Note: The parameters are estimated using Frontier 4.1 computer program.*,** ,***indicates significant at 10 per cent,5 percent and 1 per levels, respectively. Figures provided in brackets are the t values.

Table-3: Decomposition of Output Growth and TFPG in Indian Manufacturing and its Technological Sub-Categories (1998-2015)

OUTPUT ELASTICITY/

Sector	Manufacturing Total				High Technology Industries				Medium-High Tech				Medium-Low Tech				Low-Technology Industries			
	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015
ek	0.525	0.141	0.412	0.413	0.419	0.498	0.399	0.5	0.506	0.412	0.435	0.491	0.502	0.546	0.419	0.51	0.513	0.465	0.413	0.443
e_L	0.692	0.711	0.791	0.749	0.699	0.731	0.802	0.7	0.781	0.752	0.654	0.681	0.748	0.73	0.751	0.75	0.644	0.619	0.611	0.625
e	1.217	0.852	1.203	1.162	1.118	1.229	1.201	1.2	1.287	1.164	1.089	1.172	1.25	1.276	1.17	1.27	1.157	1.084	1.024	1.068
INPUT GROWTH EFFECT																				
Capital	3.7	3.88	3.54	3.41	1.01	4.01	5.14	3.08	1.98	3.15	2.88	3.01	1.98	5.06	3.55	3.81	2.44	3.29	3.13	2.03
Labour	-3.3	4.2	4.1	2.6	-5.3	4.1	1.8	-0.2	-5.9	3.8	6.3	2.9	-2.3	6	4.3	4.4	0.2	3.6	2.1	3.2
Φ	0.4	8.08	7.64	6.01	-4.29	8.11	6.94	2.88	-3.92	6.95	9.18	5.91	-0.32	11.06	7.85	8.21	2.64	6.89	5.23	5.23
SCALE EFFECT																				
e-1	0.217	-0.148	0.203	0.162	0.118	0.229	0.201	0.2	0.287	0.164	0.089	0.172	0.25	0.276	0.17	0.27	0.157	0.084	0.024	0.068
(e-1) Φ	0.09	-1.20	1.55	0.97	-0.51	1.86	1.39	0.58	-1.13	1.14	0.82	1.02	-0.08	3.05	1.33	2.18	0.41	0.58	0.13	0.36
DECOMPOSITION OF OUTPUT GROWTH																				
(1) $\dot{y}$	2.30	15.10	14.70	11.50	2.20	11.70	11.00	8.60	-0.40	15.50	18.80	12.20	3.10	18.40	14.80	15.20	4.30	14.80	11.80	10.00
(2) Φ	0.4	8.08	7.64	6.01	-4.29	8.11	6.94	2.88	-3.92	6.95	9.18	5.91	-0.32	11.06	7.85	8.21	2.64	6.89	5.23	5.23
(3) (e-1)Φ	0.22	-0.15	0.20	0.16	0.12	0.23	0.20	0.20	0.29	0.16	0.09	0.17	0.25	0.28	0.17	0.27	0.16	0.08	0.02	0.07
(4) $\Delta\delta_t$	1.07	7.01	6.28	3.53	0.04	3.03	4.38	2.12	0.09	7.04	6.80	6.11	1.29	7.16	5.51	5.77	0.15	2.82	1.99	1.14
(5) $\dot{TE}$	-0.09	1.13	1.76	1.04	0.02	0.61	0.82	0.66	-0.05	0.51	3.78	0.84	-0.03	0.33	1.98	1.85	-0.98	3.64	5.92	5.16
(6) TFP	**-0.12**	**7.99**	**8.24**	**4.73**	**0.18**	**3.87**	**5.40**	**2.98**	**0.33**	**7.71**	**10.67**	**7.12**	**1.51**	**7.77**	**7.66**	**7.89**	**-0.67**	**6.54**	**7.93**	**6.37**
(7) $\dot{y}$	1.38	16.22	15.68	10.58	-4.23	11.75	12.14	5.66	-3.88	14.50	19.76	12.86	1.19	18.55	15.34	15.83	1.81	13.35	13.14	11.53
(7) - (1)	-0.92	1.12	0.98	-0.92	-2.03	0.05	1.14	-2.94	-3.48	-1.00	0.96	0.66	-1.91	0.15	0.54	0.63	-2.49	-1.45	1.34	1.53

Source: Prepared by author using ASI, India.

Table-4: Stochastic Frontier Production Estimates for the Chinese Manufacturing Industry and its Four Technology-intensive Sub-groups

Variable	Parameter	Manufacturing Total				High Technology Industries				Medium-High Tech				Medium-Low Tech				Low-Technology Industries			
		1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015
Constant	β_0	2.04	1.07	0.99	1.09***	1.32***	1.07	0.09	1.4***	0.62***	1.04**	1.59	0.97***	1.28***	2.12***	1.07	1.17***	1.45***	2.63***	2.73	2.21***
		(1.36)	(0.43)	(2.86)	(3.41)	(5.39)	(-1.1)	(4.5)		(5.3)	(1.98)	(4.6)		(4.51)	(6.15)	(6.9)		(10.2)	(2.4)	(8.66)	
Capital	β_K	0.37	0.56	0.51	0.43***	0.02	0.71***	0.37	0.3***	0.32***	0.45***	0.35	0.28***	0.48***	0.97***	0.82	0.73***	0.19***	0.45***	0.51	0.33***
		(0.83)	(0.59)	(8.41)	(7.63)	(10.5)	(4.43)	(14.2)	(8.16)	(7.92)	(11.7)	(17.3)	(11.3)	(2.13)	(-3.5)	(-0.12)	(1.32)	(21.3)	(10.7)	(17.5)	(4.52
Labour	β_L	0.62	0.49	0.53	0.57***	0.73***	0.53***	0.47	0.56***	0.59***	0.42***	0.51	0.59***	0.59***	43.5***	-0.09	-0.09	0.75***	0.51***	0.49	0.61***
		(0.5)	(0.92)	0.81	(7.59)	(0.2)	(9.03)	5.04	(6.63)	(4.6)	(11.9)	6.7	(8.4)	(4.8)	(14.6)	13.7	(23.8)	(6.45)	(11.2)	10.2	(11.8)
K*K	β_{KK}	0.59	0.43	0.51***	0.394	0.89***	0.32***	0.66***	0.58	0.61***	0.52***	0.69***	0.43	0.29***	-0.35***	-0.09	0.4	0.75***	0.51***	0.61***	0.47
		(0.03)	(0.002)	-2.03	(-4.07)	(1.4)	(0.2)	(-0.7)	(3.7)	(-0.66)	(-1.8)	(-0.6)	(-0.30)	(-1.31)	(-5.07)	(-3.8)	(4.4)	(-0.66)	(-1.76)	(-2.8)	(-0.2)
L*L	β_{LL}	0.37***	0.14**	0.16	2.65*	1.3*	0.18*	0.99*	1.8*	0.92*	2.06*	1.8*	0.34*	2.17	4.6*	5.3**	4.8	-2.28	2.71	3.1*	1.96*
		(4.8)	(2.7)	1.8	(2.04)	(8.2)	(6.42)	9.21	(13.0)	(19.1)	(9.68)	7.8	(14.0)	(0.91)	(7.8)	3.1	(0.5)	(7.5)	(0.88)	4.03	(8.14)
K*L	β_{KL}	-0.23	0.19***	-0.22	-0.45	0.37***	2.23	0.85*	0.23	-0.73	0.27**	0.92	0.043	-0.05	0.25***	0.38***	0.67	0.53	0.14***	0.11***	0.85***
		(9.47)	(7.4)	10.2	13.3	(3.36)	(0.19)	(3.01)	(1.83)	(0.85)	(2.5)	-0.5	(0.35)	(9.5)	(7.8)	-8.9	(11.9)	(0.94)	(11.6)	-12.3	(14.1)
Time	β_T	0.04	0.06	0.05	0.04***	(54)	1.22	1.22	0.77*	0.74	0.96**	0.5	0.26	0.43**	0.23***	0.1	0.07***	-1.1	0.06***	-1.1	0.02***
		(0.37)	(0.14)	0.16	(2.65)	(1.30)	(0.18)	.99	(1.8)	(0.92)	(2.06)	1.8	(0.34)	(2.17)	(4.6)	5.3	(4.8)	(-0.84)	(2.71)	3.1	(1.96)
T*K	β_{TK}	-0.01	-0.05	-0.03	-0.01***	-0.04	-0.07	-0.07	-0.02*	-0.06	-0.04**	-0.035	-0.01	-0.04**	-0.01***	-0.1	-0.03***	0.08	-0.03***	0.08	-0.01***
		(-1.07)	(-0.43)	-1.2	(-2.4)	(-1.1)	(-0.18)	-1.08	(-1.9)	(0.91)	(-1.99)	0.54	(-0.35)	(-2.23)	(-4.64)	-0.34	(-4.1)	(0.85)	(-3.7)	1.09	(-3.24)
T*L	β_{TL}	0.02	0.002	-0.2	-0.5***	-5.34	-0.02	-3.96	-7.9	-2.84	-4.8*	-4.69	-6.54	-0.72	-0.73***	-0.72	-0.25***	-2.19	-0.3*	-2.19	-0.02
		(0.03)	(0.002)	-2.03	(-4.07)	(-1.4)	(-0.2)	-0.7	(-1.5)	(-0.66)	(-1.8)	-0.6	(-0.30)	(-1.31)	(-5.07)	-3.8	(-4.4)	(-0.66)	(-1.76)	-2.8	(-0.2)
T*T	β_{TT}	-0.01	-0.05	-0.03	-0.01***	-0.04	-0.07	-0.07	-0.02*	-0.06	-0.04**	-0.035	-0.01	-0.04**	-0.01***	-0.1	-0.03***	0.08	-0.03***	0.08	-0.01***
		(-1.07)	(-0.43)	-1.2	(-2.4)	(-1.1)	(-0.18)	-1.08	(-1.9)	(0.91)	(-1.99)	0.54	(-0.35)	(-2.23)	(-4.64)	-0.34	(-4.1)	(0.85)	(-3.7)	1.09	(-3.24)
σ^2		0.23***	0.19***	0.2	0.22***	0.37***	2.23	2.23	0.85*	0.73	0.27***	1.365	2.00	0.5***	0.25***	0.31	0.38***	0.53	0.14***	0.53	0.11***
		(9.47)	(7.4)	10.2	13.3	(3.36)	(0.19)	1.01	(1.83)	(0.85)	(2.5)	0.5	(0.35)	(9.5)	(7.8)	8.9	(11.9)	(0.94)	(11.6)	12.3	(14.1)
γ		0.07***	0.05***	0.04	0.0001	0.79***	0.96***	0.92	0.89***	0.96***	0.84***	0.6	0.97***	0.07	0.02***	0.035	0.00	0.89***	0.06	0.06***	0.02***
		(5.8)	(2.7)	1.8	(1.04)	(8.2)	(6.42)	9.21	(13.0)	(19.1)	(9.68)	7.8	(14.0)	(0.91)	(7.8)	3.1	(0.5)	(7.5)	(0.88)	4.03	(8.14)
μ		1.06	0.44	0.97	1.09**	1.32***	-0.49	0.28	0.9***	1.52***	0.49***	0.99	0.97***	3,28	3.12***	3.09	3.17***	1.41	0.63***	0.73	1.01***
		(1.36)	(0.43)	1.83	(3.86)	(5.39)	(-1.1)	(1.8)	(4.5)	(5.3)	(4.98)	2.9	(4.6)	(4.51)	(6.15)	5.1	(6.9)	(10.2)	(2.4)	4.7	(8.66)
η			0.002	0.5***	0.03	0.34	0.02	0.9	0.8		0.08*	0.54	0.03		-0.73***	0.25	0.03		0.3*	-0.02	0.003
			(0.002)	(4.07)	(5.07)	(1.4)	(0.2)	(1.5)	(3.85)		(1.8)	(0.30)	(3.87)		(-5.07)	(2.4)	(0.01)		(1.76)	(- 0.8)	(5.1
LLF		-420.8	-436.3	-635.9	-862.5	-68.6	87.1	-115.1	-143.1	-79.0	-71.9	96.3	-137.9	-167.8	-139.8	-203.3	-302.3	-46.6	-139.5	-93.1	319.9
Nobs		156	312	208	624	18	36	24	72	45	90	45	180	33	66	44	132	60	120	80	240

Source: Prepared by author using CDO,China. Note:The parameters are estimated using Frontier 4.1 computer program. *, **, *** indicates significant at 10 per cent, 5 percent and 1 per levels, respectively. Figures provided in brackets are the t values.

Table-5: Decomposition of Output Growth and TFPG in Chinese Manufacturing and its Various Sub-Sectors (1999-2015)

OUTPUT ELASTICITY	Manufacturing Total				High Technology Industries				Medium-High Tech				Medium-Low Tech				Low-Technology Industries			
Sector	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015	1998-2005	2005-2010	2010-2015	1998-2015
e_K	0.425	0.41	0.309	0.374	0.327	0.42	0.382	0.335	0.346	0.367	0.33	0.356	0.372	0.395	0.365	0.354	0.398	0.37	0.359	0.372
e_L	0.612	0.641	0.696	0.629	0.688	0.7	0.734	0.704	0.681	0.652	0.68	0.671	0.648	0.632	0.662	0.652	0.644	0.65	0.681	0.645
e	1.037	1.051	1.005	1.003	1.015	1.12	1.116	1.039	1.027	1.019	1.01	1.027	1.02	1.027	1.027	1.006	1.042	1.02	1.04	1.017
INPUT GROWTH EFFECT																				
Capital	2.9	3.01	3.02	3.21	3.01	2.01	2.14	3.08	3.98	3.15	2.87	3.01	2.98	2.76	3.33	3.01	2.14	3.89	4.13	2.78
Labour	1.09	1.91	1.8	2.7	1.38	1.12	1.98	2.12	0.89	1.06	1.13	1.004	1.04	1.94	1.55	1.07	1.01	1.67	1.39	1.48
$\Phi^{\cdot}$	3.99	4.92	4.82	5.91	4.39	3.13	4.12	5.2	4.87	4.21	4	4.014	4.02	4.7	4.88	4.08	3.15	5.56	5.52	4.26
SCALE EFFECT																				
e-1	0.037	0.051	0.005	0.003	0.015	0.12	0.116	0.039	0.027	0.019	0.01	0.027	0.02	0.027	0.027	0.006	0.042	0.02	0.04	0.017
(e-1) $\Phi^{\cdot}$	0.15	0.25	0.02	0.02	0.07	0.38	0.48	0.20	0.13	0.08	0.05	0.11	0.08	0.13	0.13	0.02	0.13	0.09	0.22	0.07
DECOMPOSITION OF OUTPUT GROWTH																				
(1) $\dot{y}$	9.20	15.20	11.60	14.50	15.70	7.90	8.30	12.80	10.10	16.30	8.90	14.50	9.40	24.00	11.90	19.40	1.50	12.40	17.20	11.30
(2) $\Phi^{\cdot}$	3.99	4.92	4.82	5.91	4.39	3.13	4.12	5.20	4.87	4.21	4.00	4.01	4.02	4.70	4.88	4.08	3.15	5.56	5.52	4.26
(3)(e-1) $\Phi^{\cdot}$	0.15	0.25	0.03	0.02	0.07	0.38	0.48	0.16	0.13	0.08	0.05	0.11	0.08	0.10	0.13	0.02	0.13	0.09	0.21	0.07
(4) $\Delta\delta_t$	5.67	7.81	5.18	6.53	8.41	4.03	4.18	5.12	6.89	6.54	5.77	6.41	3.79	1.16	2.01	3.77	2.15	5.32	8.87	4.13
(5) $T\dot{E}$	-0.64	2.24	1.76	2.04	1.62	0.80	0.74	2.82	-1.65	5.02	-0.78	3.34	1.23	16.33	4.48	10.85	-2.98	0.12	1.82	2.76
(6)$TF\dot{P}$	5.17	10.30	6.97	8.59	10.09	5.21	5.40	8.10	5.37	11.64	5.04	9.86	5.10	17.59	6.62	14.65	-0.70	5.53	10.69	6.96
(7) $\dot{y}$	9.16	15.22	11.79	14.50	14.48	8.34	9.52	13.30	10.24	15.85	9.04	13.87	9.12	22.29	11.50	18.73	2.45	11.09	16.21	11.22
(7)-(1)	-0.04	0.02	0.19	0.00	-1.22	0.44	1.22	0.50	0.14	-0.45	0.14	-0.63	-0.28	-1.71	-0.40	-0.67	0.95	-1.31	-0.99	-0.08

Source: Prepared by author using CDO, China.

periods , 1999-2005, 2005-2010, 2010-2015 and period as a whole 1999-2015 has been presented in Table-4.6 for China's manufacturing sector. The estimated coefficient of time varying technical inefficiency has been mostly positive for all sub periods and all sub-groups of manufacturing sector except for a negative coefficient of medium low-techn industries during 2005-10 and low-tech industries showing negative coefficient of inefficiency decay in the initial phase and during 2005-10 also. The time varying technical (in)efficiency parameter has been found to be 0.02. It implies that rate of technical efficiency in Chinese manufacturing has during 1998-2015 has been increasing to the extent of 3.0 per cent. The estimates of time coefficient show significant technical progress in all sub-categories of Chinese manufacturing during 1999-2015. The other two parameters γ and σ^2 associated with the variance of the random variable V_{it} and U_{it} show a significance difference in the realised output from potential output. The difference has been mainly due to the difference in the industry specific technical efficiency and not due to any random changes.

In Table-4, reports the estimated values of the output elasticity with respect to the inputs of capital and labour are reported. Returns to scale, input growth, adjusted scale effect, rate of technical progress and growth of technical efficiency have also been estimated for China's manufacturing. As shown in Table-4.7, labour has the greater output elasticity as compared to capital. For manufacturing as whole the output elasticities for labour and capital have been .629 and .374 during 1999 to 2015. Output elasticity of capital has been decreasing over the years which hints towards low productivity of capital in Chinese manufacturing whereas output elasticity of labour has shown improvement.

The estimates of these elasticities show similar trends for sub-groups of manufacturing sector considered here. Input growth has been highest in H-T sector in which capital made more contribution towards input growth.

Now if we look at industry wise technical efficiency change in various sub-periods it becomes clear that in the initial phase, manufacturing sector as a whole witnessed negative technical efficiency change. It was during 2005-10 that most of the technical efficiency improvement happened in all industries with M-L-T industries taking the lead in technical efficiency improvement. L-T industries showed lowest technical efficiency improvement during 1998-2015.

Technical progress has surpassed input growth in Chinese manufacturing during 1998-2015. M-H-T industries have shown the highest rate of technical progress followed by H-T industries and technical progress contributed more towards output growth. H-T sector of Chinese manufacturing seems to have acquired the dynamism which could have been the result of improvement in research and technical efficiency in this sector. M-L-T and L-T industries showed quite lower technical progress. L-T industry of Chinese manufacturing has been experiencing both low technical progress and technical efficiency as compared to other sectors of manufacturing industry of China during 1999-2015.

Conclusion

China's impressive performance in the manufacturing sector has stunned the world even as it increased its cheaply produced exports across the world. Indian economy on the other hand could not replicate the growth experience of the developed economies that followed traditional growth path. Using the growth decomposition method used present study estimated the contribution from input growth, scale effect, technical progress and technical efficiency towards output growth. Labour input showed higher elasticity as compared to capital in both economies but its contribution towards input growth has been lower. In terms of elasticity both labour and capital showed increasing returns for both economies at all points of time. In analysing TFPG growth it has been found that technical progress has played major role in both economies and both lacking at efficiency front with India being behind China. China's manufacturing has shown higher TFPG and efficiency in H-T industries whereas L-T industries showed inefficiency effects. Whereas Indian manufacturing seemed to be backed up by high technical progress in M-L-T industries. In Indian economy technical progress failed to surpass the contribution of input growth towards output growth whereas China's manufacturing showed significantly more contribution by TFPG in output growth of the manufacturing sector.

In a nutshell, it can be said that the challenge for India lies in strengthening its L-T and labour intensive base first so as to take the advantage of low labour cost and its vast labour pool. In India L-T industries have shown improved efficiency but this has been accompanied by low technical progress. India needs a firm base in low end products in the value chain so as to embark on the path of high end product manufacturing with high rate of technical progress and higher technical efficiency. The challenge for further industrial growth in China seems to be quality and improving efficiency. China needs to implement measures to narrow down the efficiency gap and keep the technical progress emulating through leaning by doing, absorbing advanced technology and improving efficiency of manufacturing processes.

References

Battese, G. E. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis*, 3(1-2), 153-169.

Battese, G. E. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20(2), 325-332.

Battese, G. E., & Coelli, T. J. (1988). Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data. *Journal of Econometrics*, 38(3), 387-399.

Chenery, H. (1960). Patterns of industrial growth. *American Economic Review 50*, 624-654.

Chenery, H. B., & Taylor, L. (1968). Development Pattern: Among countries and Across time. *The Review of Economics and Statistics, 50*(4), 391-416.

Chenery, H., & Syrquin, M. (1975). Patterns of development 1950-1970 (English). *A World Bank Research Publication*. New York: Oxford University Press.

Chenery, H.B. (1955). The Role of Industrialization in Development Program', *The American Economic Review*, *45* (2).

Herd, R., & Dougherty, S. (2007). Growth Prospects in China and India Compared. *The European Journal of Comparative Economics*, *4*(1), 65-89.

Hirschman, A. (1958). *The Strategy of Economic Development*. New Haven: Yale University Press.

Hirschman, A. O. (1964). The Paternity of an Index. *American Economic Review, 54*(5), 761-762.

Hoffmann, W.G. (1958). *The Growth of Industrial Economies*. UK: Manchester University Press.

Holz, C. (2006a). China's Economic Growth 1978-2025: What we know today about China's Economic Growth Tomorrow (Working Paper 8). Hong Kong: Centre on China's Transnational Relations, Hong Kong University of Science and Technology.

Holz, C. (2006b). New Capital Estimates for China. *China Economic Review, 17*(2), 142- 185.

Imbs, J., &Wacziarg, R. (2003). Stages of Diversification. *The American Economic Review, 93*(1), 63-86.

Kathuria, V. R., Rajesh, S. N., & Sen, K. (2013). Productivity Measuring in Indian Manufacturing: A Comparison of Alternate Methods. *Journal of Quantitative Economics*, 11(1&2), 148-179.

Kumbhakar, S. (1990). Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency. *Journal of Econometrics*, *46*(1/2), 201-212.

Kumbhakar, S. C., & Lovell, K.C.A. (2000). *Stochastic Frontier Analysis*. Cambridge: Cambridge University Press.

Lall, S. (2001). Competitiveness Indices and Developing Countries: An Economic Evaluation of the Global Competitiveness Report. *World Development*, 29(9), 1501-1525.

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Impact of Workplace Ostracism, Emotion Exhaustion on Employee Engagement and Employee Wellbeing Among IT Women Professionals in India

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Abstract

Workplace ostracism is when a worker is rejected and disregarded by other workers in the same workplace. Employee performance is affected since this situation inhibits their ability to succeed. The fundamental objective of this study is to evaluate the effects of workplace ostracism, emotion exhaustion on employee engagement and employee wellbeing among IT women professionals working in IT companies located in various states in Southern India. Data were obtained from 260 IT women professionals from various IT companies in the states of southern India. The obtained data were analysed by using exploratory factor analysis, confirmatory factor analysis and structural equation modelling to test hypotheses. It was found that workplace ostracism has a significant and negative impact on emotional exhaustion. Workplace ostracism have a non-significant and does not have a positive significant impact on employee engagement. Emotional exhaustion has a significant and negative impact on employee engagement. Employee engagement has a significant and positive impact on employee wellbeing.

Keywords: Employee Engagement, Employee Wellbeing, Emotion Exhaustion and Workplace Ostracism

Introduction

The term "ostrakismos" from ancient Greek denotes the practice of expelling those with despotic ambitions from democratic states, giving rise to the term "ostracism" (Zippelius, 1986). Workplace ostracism, also recognized as "cold violence" in professional contexts, refers to the perceived rejection experienced at workplace by an employee from their

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colleagues (Ferris, Brown, Berry, & Lian, 2008). It results in increased levels of depression and decreased satisfaction among employees (Hitlan, Cliffton, & DeSoto, 2006). From the perspective of organizational behavior and social psychology, this concept encompasses four distinct connotations: At first,Workplace ostracism can be characterized as a type of social exclusion experienced by employees in professional environments "workplace cold violence" and "workplace cold treatment," encompassing several aspects such as mental abuse, psychological manipulation, interpersonal apathy, damage to self-esteem, and the imposition of unfair treatment. Furthermore, workplace ostracism relates to the employee subjective psychological perception, and the extent to which they encounter workplace ostracism depends on their own subjective evaluation. Furthermore, workplace ostracism encompasses the pervasive sense of exclusion experienced by employees. The source of rejection lacks clarity and specificity. In a broad sense, the individuals who may serve as sources of rejection for individuals in a professional setting include their superiors, peers, subordinates, and clients with whom they interact. Workplace ostracism is a prevalent occurrence in professional settings, characterized by interpersonal exclusion inside the workplace. Workplace ostracism results in the denial of employees' entitlement to recognition and engenders a diminished sense of their presence inside the business, leading to a state of "social death." The experience of depression and pessimism not only has a detrimental impact on individuals' psychological well-being, but also hinders the fulfillment of their fundamental requirements. Consequently, these factors significantly influence the behaviors exhibited by employees inside the workplace (Y. Xing & Yongzhou 2022).Two forms of workplace ostracism exist: intentional and unintentional. Intentional ostracism involves a person purposefully ignoring someone, being aware of their behavior, and intending to harm or target the individual. The silent treatment is a common manifestation of intentional ostracism in professional settings(Williams, Bernieri, Faulkner, Gada-Jain, & Grahe, 2000). People who do not purposefully ignore others are engaging in non-purposeful ostracism. Individuals engaging in workplace ostracism may not realize that their actions are causing harm to others(Sommer, Williams, Ciarocco, & Baumeister, 2001). Burnout and emotional exhaustion are associated with various undesirable psychological and professional consequences. Individuals experiencing either condition exhibit lower job performance and are more likely to resign from their positions. Emotional exhaustion is also linked to a higher chance of depression and other detrimental psychological outcomes. Symptoms such as disinterest and lack of enthusiasm towards people, places, and objects in one's immediate surroundings, along with feelings of physical and mental fatigue and reduced energy, are indicative of emotional exhaustion, reflecting an individual's distressing emotional state. This condition is commonly understood as a depletion of resources (Boswell, Olson-Buchanan, & LePine, 2004; Watkins et al., 2015). As per the conservation of resource theory, resource depletion imposes additional strain on the individual, necessitating greater resource investment to offset further losses (Halbesleben, Neveu, Paustian-Underdahl, & Westman, 2014). Once resources are depleted, it may trigger a cascade of ongoing losses, resulting in a negative spiral of effects (Sun & Pan, 2008; Whitman, Halbesleben, & Holmes IV, 2014).Worldwide organizations' existence and growth depend heavily on the well-being of their workforce(Spreitzer & Porath, 2012) and has become a significant area of study in organizational behavior and related fields. According to (Warr, 1987), employee wellbeing includes a person's assessment of the general value of their professional experience and job outcome. (Zheng, Zhu, Zhao, and Zhang, 2015) categorise well-being into three categories: living, psychological, and work-related, providing a more comprehensive understanding of individuals' wellbeing status.

Review of Literature

Workplace Ostracism

Various definitions of workplace ostracism can be found in existing literature(Ferris et al., 2008; Williams et al., 2000). Organizational ostracism in the workplace is defined as "the individual's feeling of being ignored or ostracized by others" (Robinson, O'Reilly, & Wang, 2013).

The term "workplace ostracism" refers to when employees feel disregarded by their co-workers (Ferris et al., 2008). Workplace ostracism has been found to have a negative association with multiple organizational factors, including commitment, performance, employee engagement, turnover intentions, organizational citizenship behavior, as well as individual factors such as employee needs, humor, overall well-being, and stress. Additionally, it contributes to the occurrence of daily hassles in the workplace.

The practice of ostracism within the workplace has been found to have a negative impact on productivity levels, leading to a decrease in overall productivity. Additionally, it has been observed that ostracism also contributes to an increased inclination among employees to leave their current positions, hence promoting turnover within the organization. The long-term impact of this phenomenon not only has a negative impact on organizational performance but also undermines its brand reputation in the labor market (Chung & Yang, 2017), additionally influencing employer reputation.

Ostracized employees are more likely to feel disconnected from their team or the organization as a whole. It makes individuals feel unnecessary to their organization if it is not effectively managed with coping mechanisms such as humour promotion and organizational support, or using design interventions at the organizational level to minimize its negative effects, or by introducing various team or group level interventions that may result in improved coordination, team-building, and contribute to promoting overall employee wellbeing. Being ostracised at work is recognized as a form of "social pain" because it is an unpleasant and painful experience for the individual (Riva, Wirth, & Williams, 2011)and has devastating repercussions at the organizational and individual levels (Ferris et al., 2008). Research has indicated that being ostracized at work has an impact on an individual's physical and mental health (Fatima, 2016) organizational commitment (Hitlan et al., 2006), and individuals who experience ostracism show more deviant behavior and think about quitting more (O'Reilly, Robinson, Berdahl, & Banki, 2015).

Emotional Exhaustion

The majority of research on emotional exhaustion focuses on its correlation with job satisfaction and burnout. Burnout, as defined by (Maslach and Jackson,1981), is characterized by emotional exhaustion and cynicism, particularly common among individuals engaged in "people-work," with emotional exhaustion being its defining characteristic (Wright & Bonett, 1997; Wright & Cropanzano, 1998). When someone feels they have exhausted their emotional reserves and are no longer able to psychologically support others, it is known as emotional exhaustion (Maslach & Jackson, 1981), resulting in a persistent state of reduced emotional capacity due to prolonged hard work (Wright & Cropanzano, 1998).

Emotional exhaustion has been connected to various negative physiological, psychological, and work-related outcomes. It can lead to decreased self-care quality among staff, absenteeism, job turnover, physical exhaustion, low morale, poor sleep, increased drug and alcohol consumption, as well as difficulties in familial and marital relationships (Maslach & Jackson, 1981). Moreover, feeling emotionally drained results in negative employment-related outcomes such as role conflict, thoughts of changing jobs or careers, and actual job turnover (Jackson, Schwab, & Schuler, 1986).

Workplace ostracism contributes to the weakening of individuals' psychological and emotional reserves, leading to emotional exhaustion (Chen & Li, 2020; Jahanzeb & Fatima, 2018). The theory of conservation of resources holds that people work hard to obtain, preserve, and secure resources; when these resources are endangered or depleted, they become stressed and exhausted. Emotional exhaustion may arise from a failure to immediately replace depleted resources (Hobfoll, 2001). Furthermore, workplace ostracism severs employees' emotional connections with their colleagues. Emotional communication through social interactions is essential for strengthening emotional resources and maintaining mental and physical health (Heaphy & Dutton, 2008).A prominent sign of psychological overwork is emotional exhaustion, which lowers employees' sense of wellbeing and leaves them with less emotional and psychological resources.

According to affective event theory, individual emotional reactions to upsetting emotional events shape their attitudes and behaviours (Ashkanasy, Ayoko, & Jehn, 2014; Weiss & Cropanzano, 1996). Employees who are emotionally drained are more likely to show signs of unhappiness and dislike for their professions and lives, which might result in turnover intention and lower levels of life satisfaction (Chen & Li, 2020). Emotional exhaustion is a poor index of employee well-being and reflects personal psychological states and health (Kausto, Elo, Lipponen, & Elovainio, 2005). According to social exchange theory, when individuals view being laid off as a bad emotional experience, their emotional reserves become exhausted, which eventually lowers their well-being (Imran, Fatima, Sarwar, & Iqbal, 2023; Liu & Xia, 2016).Therefore, this research suggests that individuals' emotional exhaustion increases with the extent of workplace exclusion they experience, impacting their well-being and that of those around them.

Employee Engagement

Organizations invest resources in cultivating a culture of work engagement due to its impact on various organizational factors, employee performance, organizational climate, and profitability. Highly engaged employees are more likely to provide outstanding customer service, which encourages repeat business and boosts sales income, thus improving total profitability (Perrin, 2003). Employee engagement significantly contributes to employee well-being and satisfaction. Organizations that prioritize employee involvement in decision-making processes and transparently communicate challenges and achievements foster a sense of value among employees, thereby promoting positive emotions. Furthermore, such engagement benefits the organization by fostering a more productive workforce, as content and healthy employees tend to outperform their unhappy and unhealthy counterparts (Mauno, Kinnunen, & Ruokolainen, 2007).

Employee engagement represents the relationship between employees and the organization; stronger relationships correlate with greater organizational success, as motivated workers develop a deep emotional connection with their company and invest time, effort, and high-quality work (Nagtegaal & Quirke, 2008). Workplace ostracism diminishes employee engagement, subsequently reducing service levels. Ignoring an employee affects customer satisfaction because the individual is unable to perform their job effectively (Leung, Wu, Chen, & Young, 2011). Negative associations exist between workplace ostracism and job satisfaction, organizational commitment, and employee engagement (Nielsen & Einarsen, 2012). Ostracism at work correlates positively with burnout and intentions to leave. Engaged employees typically exhibit high energy levels and a strong professional identity (Bakker, Schaufeli, Leiter, & Taris, 2008). Employee engagement and workplace exclusion are negatively correlated, as evidenced by its detrimental effect on employees' work engagement (Glasø, Bele, Nielsen, & Einarsen, 2011; Reio Jr & Sanders-Reio, 2011).

Employee Wellbeing

Employee well-being encompasses workplace well-being, life well-being, and psychological well-being. It's a term that, as (Lyubomirsky (2001)) suggests, is challenging to precisely define but universally understood. Philosophically, two main perspectives exist: Hedonism, which equates well-being with subjective happiness and eudaimonism which equates well-being as the realization of human potential through self-actualization and personal achievement.

Workplace ostracism significantly influences an individual's well-being(Ryan & Deci, 2001). Well-being is multifaceted, involving emotional reactions, domain satisfactions, and overall life satisfaction. It encompasses both positive (e.g., joy) and negative (e.g., suffering) experiences(Diener, Suh, Lucas, & Smith, 1999). Ostracism in the workplace is marked by a lack of social engagement, causing individuals to feel undervalued and doubtful of themselves(Robinson et al., 2013). Subjective well-being, based on personal standards, includes life satisfaction and emotional experiences, such as positive and negative emotions (Diener, 1984, 2000).

Employee well-being relates to an individual's psychological state at work and their overall quality of life (Siegrist, Wahrendorf, Von Dem Knesebeck, Jürges, & Börsch-Supan, 2007; Vanhala & Tuomi, 2006). Scholars like (Ilies, Schwind, and Heller, 2007) emphasize individual and situational factors in defining employee well-being, distinguishing between work-related and non-work-related aspects. Considering an employee's health, employment, family relationships, and life satisfaction is crucial in measuring well-being (Siegrist et al., 2007; Vanhala & Tuomi, 2006). Employee well-being can encompass various dimensions, including work satisfaction, family satisfaction, life satisfaction, and positive emotions (Lu, Gilmour, Kao, & Huang, 2006).

Ostracized employees struggle to receive support from colleagues, impacting their well-being across work, psychology, and life domains.

Workplace ostracism often involves punitive measures, diminishing organizational commitment and hindering positive experiences at work and in life(Ferris, Lian, Brown, & Morrison, 2015; Howard, Cogswell, & Smith, 2020; Jiang & Poon, 2023; Zhu, Lyu, Deng, & Ye, 2017). According to belongingness theory, ostracism disrupts employees' sense of belonging to the work team, affecting their psychological, behavioral, and work-related outcomes(Howard et al., 2020; Imran et al., 2023; Wu, Yim, Kwan, & Zhang, 2012). Overall, workplace ostracism significantly impacts employee well-being across various dimensions. The following are the four assumptions/hypotheses:

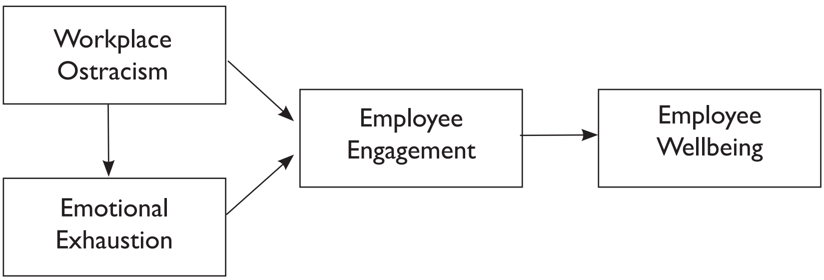
H_1: Workplace Ostracism have a negative impact on Emotional Exhaustion

H_2: Workplace Ostracism have a positive impact on Employee Engagement

H_3: Emotional Exhaustion have a negative impact on Employee Engagement

H_4: Employee Engagement have a positive impact on Employee Wellbeing

Figure-1: Conceptual Framework



Compiled by the Researcher

Materials and Methods

Research Methodology

Data Collection

Hypotheses was tested using a self-administered questionnaire. The researchers focused on IT women professionals in the IT companies located in various states in Southern India. Convenience sampling method is used to draw the samples. Two hundred sixty (270) questionnaires were distributed among women employees. Finally, after eliminating unfilled questionnaires, 260 were taken for further analysis.

Scaling

Participants' genuine responses for each component were assessed using a

5-point Likert scale (Finstad, 2010). The measurement scales used for each construct were as follows:

- Workplace Ostracism (WPO) construct was measured using the Workplace Ostracism Scale developed by(Ferris et al., 2008). The scale ranged from 'Strongly Disagree' (rating 1) to 'Strongly Agree' (rating 5). Sample items included 'Others avoided you at work' and 'Others refused to talk to you at work'.
- Emotional Exhaustion (EMO_EXH) construct was measured using the Emotional Exhaustion Scale developed by(Meghan, 2014). The scale ranged from 'Strongly Disagree' (rating 1) to 'Strongly Agree' (rating 5). Sample items included 'I feel emotionally drained by my work' and 'I feel frustrated by my job'.
- Employee Engagement (EMP_ENG) construct was measured using the Employee Engagement Scale developed by(Vale, 2011). Sample items of the scale included 'At work, I have the opportunity to do what I do best every day' and 'There is someone at work who encourages my development'.
- Employee Well-being (EMP_WELL) construct was measured using the Employee Wellbeing Scale developed by(Zheng et al., 2015). Sample items included 'I am satisfied with my work responsibilities' and 'In general, I feel fairly satisfied with my present job'.

The suggested conceptual framework was assessed through the use of Exploratory Factor Analysis (EFA) in SPSS version 26. Using AMOS 23, structural equation modelling (SEM) and confirmatory factor analysis (CFA) were utilized in assessing each construct's validity and reliability as well as to test the suggested theories. The suggested hypotheses were then evaluated using the structural model by the researchers after first running the measurement model to verify each construct's validity and reliability.

Results

Table-1: Demographic Distribution of the Respondents

Demographic	Categories	Frequency (n)	Percent (%)
Age	Below 30 years	56	21.5
	31 to 40 years	132	50.8
	Above 40 years	72	27.7
	Below 30 years	56	21.5
Educational qualification	Graduate	71	27.3
	Post-graduate	97	37.3
	Professional degree	92	35.4

Demographic	Categories	Frequency (n)	Percent (%)
Family type	Joint	141	54.2
	Nuclear	119	45.8
Experience	Less than 3 years	61	23.5
	3 to 6 years	123	47.3
	Above 6 years	76	29.2
Nature of work	Management	64	24.6
	Technical	83	31.9
	Business development	70	26.9
	Support functions	43	16.5
Role in Company	Team member	43	16.5
	Team leader	97	37.3
	Project manager	61	23.5
	Project leader	59	22.7

Source: Primary data

Table-1 shows the distribution of demographic variables. Out of 260 women professionals, 50.8% of them belongs to the age group between 31-40 years of age. 37.3% of them completed their post-graduation. 56.2% of them were single. 54.2% of them lives in joint family. 47.3% of them have 3-6 years of work experience. 31.9% of the respondents engaged in technical department, 26.9% of them work in business development department, 24.6% of them work in management department and 16.5% of them work in support function department. 37.3% of them work as team leaders, 23.5% of them work as project manager, 22.7% of them work as project leader and 16.5% of them work as team member in their IT companies.

Principal Component Factor Analysis

Principal component analysis was used to carry out factor analysis. A substantial p-value of 0.000 was obtained from the Bartlett sphericity test, showing that the correlation matrix was appropriate for factor analysis. The data's Kaiser-Meyer-Olkin (KMO) value of 0.865 indicated that the sample was adequate. Four principal components were extracted, with a cumulative explanation of 88.574% of the total variance, indicating that the extracted components explained a significant portion of the variance in the data. This implies that the scale has strong validity. The factor loading matrix following varimax rotation which is shown in Table-2, provides insight into how each item correlates with the extracted components.

Reliability and Validity of Constructs

To evaluate internal consistency reliability and validity, the researchers utilized the measurement model. Composite reliability was employed to assess internal consistency reliability. Furthermore, cross-loadings were investigated to verify discriminant validity, and Average Variance Extracted (AVE) was utilized to assess convergent validity.

Construct Reliability and Validity Analysis

Accordingly, the factor loadings, construct reliability and validity results are shown in Table-2.

Table-2: Construct Reliability and Validity Results

Constructs	Factor loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Workplace Ostracism				
WPO1	0.961	0.973	0.967	0.855
WPO2	0.927			
WPO3	0.922			
WPO4	0.908			
WPO5	0.904			
Emotional Exhaustion				
EMO_EXH1	0.929	0.969	0.961	0.859
EMO_EXH2	0.929			
EMO_EXH3	0.927			
EMO_EXH4	0.923			
Employee Engagement				
EMP_ENG1	0.953	0.917	0.943	0.846
EMP_ENG2	0.927			
EMP_ENG3	0.878			
Employee Wellbeing				
EMP_WELL1	0.877	0.904	0.902	0.755
EMP_WELL2	0.869			
EMP_WELL3	0.860			

Internal Consistency Reliability

The Cronbach's Alpha values for the constructs were as follows: Workplace Ostracism (WPO) was 0.973, Emotional Exhaustion (EME) was 0.969, Employee Engagement was 0.917, and Employee Wellbeing was 0.904. All four constructs met the accepted threshold value for Cronbach's Alpha reliability, which is 0.7(Hair Jr et al., 2021).

Convergent Validity

Convergent validity, as defined byHair, Black, Babin, Anderson, and Tatham (2010), refers to the degree to which one indicator positively correlates with other indicators of the same construct. This is assessed using factor loadings and Average Variance Extracted (AVE). According to the guidelines, the AVE value should be 0.50 or higher. Additionally, factor loading values equal to or greater than 0.4 are considered acceptable if the AVE scores exceed 0.5(Hulland, 1999). In the present research study, the AVEs of the constructs and factor loadings of the indicators met the recommended criteria outlined by(Hair Jr et al., 2021).

Discriminant Validity

(Fornell and Larcker, 1981) proposed the traditional metric, which states that the shared variance between all model constructs should not exceed their AVEs. The squared variance within each construct, or the square root of AVE, should be compared to the inter-construct correlation of that construct and all other reflectively measured constructs in the structural model. Consequently, a bigger square root of AVE of a construct in relation to its correlation with every other construct in the study indicates discriminant validity. The measurement model's discriminant validity is shown in Table-3.

Table-3: The Measurement Model's Discriminant Validity

	Workplace Ostracism	**Emotional Exhaustion**	**Employee Engagement**	**Employee Wellbeing**
Workplace Ostracism	(0.924)			
Emotional Exhaustion	0.423**	(0.926)		
Employee Engagement	0.408**	0.314**	(0.919)	
Employee Wellbeing	0.112	0.116	0.203**	(0.868)

** Correlation is significant at the 0.01 level (2-tailed). *Figures in () denote the SQRT of AVE.*

Confirmatory Factor Analysis

The degree of fit between the actual data obtained from the questionnaire scale and the proposed factor structure model was evaluated in this study using confirmatory factor analysis (CFA), which helped to determine whether the index variables could adequately represent latent variables. Good convergent validity is demonstrated by the results in Table-2, which indicates that the Average Variance Extracted (AVE) of emotional tiredness, workplace ostracism, employee engagement, and employee wellbeing are all higher than 0.55.

The study used structural equation modelling software called AMOS 23 to test the path hypotheses in the model after establishing the validity and reliability of each measurement scale. The fit indices of the model were as follows: X2/DF = 1.893; RMR = 0.043; GFI = 0.927; AGFI = 0.895; NFI = 0.966; IFI = 0.984; CFI = 0.984; RMSEA = 0.059. Acceptability of the established model was confirmed by the evaluation model's X2/DF, RMR, and RMSEA values, which were all within a reasonable range, and by additional fit indices that showed a decent fit. Table-4 illustrates the confirmatory factor analysis model's fitting indices.

Figure-2: Measurement Model

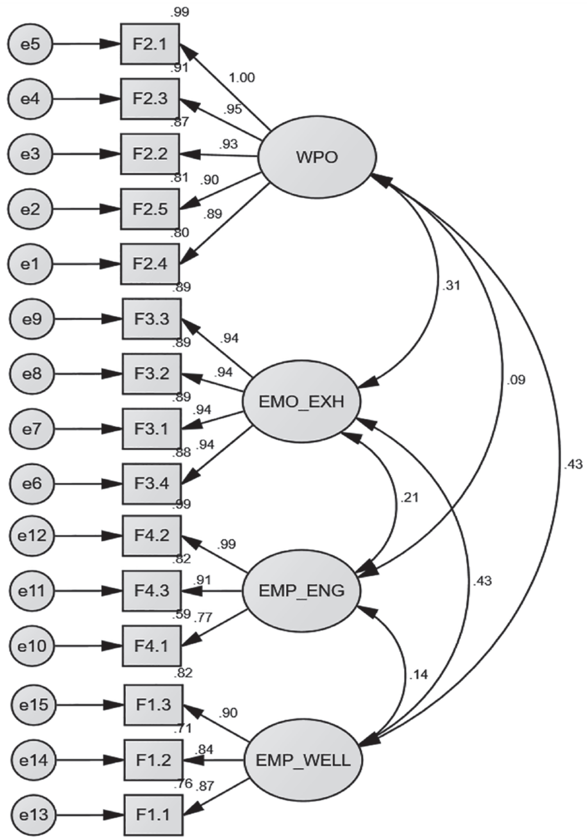
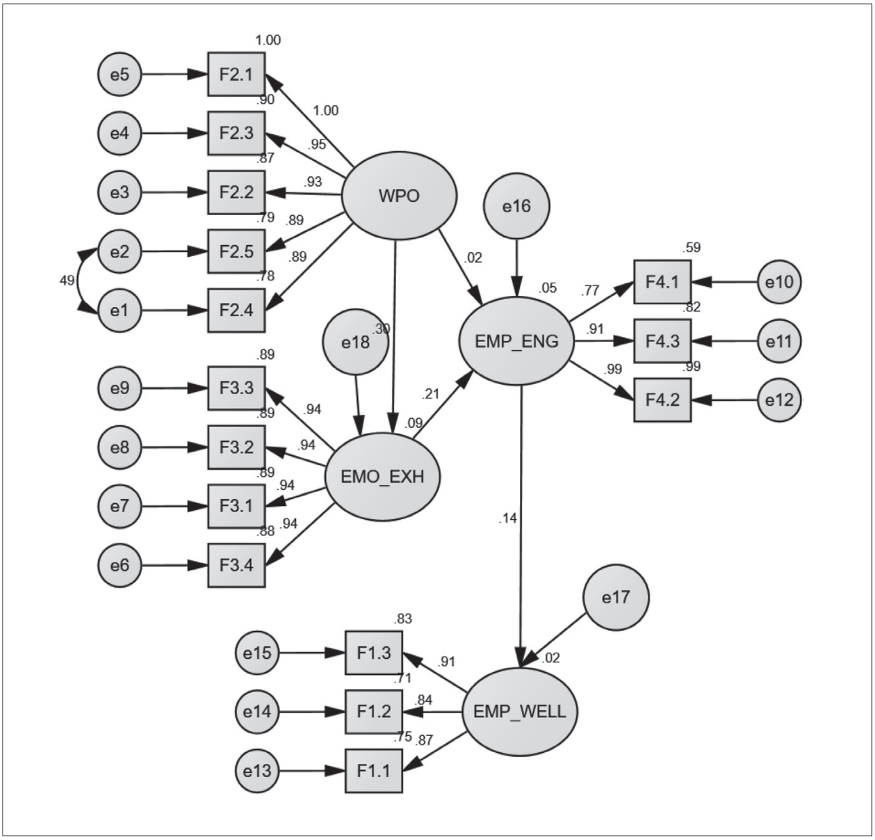


Table-4: Fit Indices of CFA Model

Indices	Threshold Values	Inspection Result Data	Model Adaptation Judgment
X^2/df	<3.00	1.893	Yes
RMR	<0.05	0.043	Yes
GFI	>0.90	0.927	Approx. 0.9
AGFI	>0.90	0.895	Approx. 0.9
NFI	>0.90	0.966	Approx. 0.9
IFI	>0.90	0.984	Approx. 0.9
CFI	>0.90	0.984	Approx. 0.9
RMSEA	<0.08	0.059	Yes

Structural Equation Modelling

Figure-3: Normalized Path Results



Structural Equation Analysis

The estimation of workplace ostracism, emotional exhaustion, employee engagement and employee wellbeing model are primarily accomplished by path analysis, which focuses on assessing the reliability and strength of the causal relationship. Collected data has been imported into the model and analysed to get Figure-2. A substantial relationship between WPO and EMO_EXH is indicated by P values less than 0.001; WPO and EMP_ENG are more than 0.05, indicating no significant correlation; and between EMO_EXH and EMP_ENG, between EMP_ENG and EMP_WELL, are less than 0.05, indicating a significant correlation between them. These results, along with the fact that all of the standardized coefficients are positive, pass the hypothesis test. P value is less than 0.05, indicating a substantial negative influence of WPO on EMO_EXH. H1 states that WPO have a negative impact on EMO-EXH and hence H1 is supported. WPO have a positive impact on EMP_ENG, p value is more than 0.05 and it is not significant. H2 states that WPO do not have a positive significant impact on EMP-ENG and hence H2 is not supported. EMO_EXH have a negative impact on EMP_ENG, p value is less than 0.05 and it is significant. H3 states that EMO_EXH have a negative impact on EMP_ENG and hence H3 is supported. EMP_ENG have a positive impact on EMP_WELL, p value is less than 0.05 and it is significant. H4 states that EMP_ENG have a positive impact on EMP_WELL and hence H4 is supported.

Table-5: Normalized Path Coefficient Analysis

	Hypotheses			Esti-mate	Stan-dardized Estimate	SE	CR	*P*	Results
H_1	EMO_EXH	←	WPO	0.304	0.300	0.062	4.882	***	Supported
H_2	EMP_ENG	←	WPO	0.019	0.021	0.058	0.331	0.741	Not Supported
H_3	EMP_ENG	←	EMO_EXH	0.188	0.209	0.060	3.151	0.002	Supported
H_4	EMP_WELL	←	EMP_ENG	0.137	0.137	0.066	2.085	0.037	Supported

***P<0.001 (Note: WPO- Workplace Ostracism, EMO_EXH – Emotional Exhaustion, EMP_ENG – Employee Engagement, EMP_WELL – Employee Wellbeing).

Discussions and Conclusion

The study initially investigates the relationship between workplace ostracism and emotional exhaustion. It was found that workplace ostracism has a significant and negative impact on emotional exhaustion, confirming hypothesis H1. Ostracism at work is seen as a stressor that causes employees' emotional reserves to run low and negatively impacts their attitudes and actions. The result aligns with the theory that increased effort-reward imbalance leads to enhanced emotional weariness (Wright & Cropanzano, 1998). Employees suffering from emotional dissonance frequently exhibit superficial behavior, wherein they hide negative feelings while exhibiting positive ones, particularly when working with customers who are demanding or challenging. Individuals who display a superficial act at work often become emotionally drained and run out of emotional reserves (Hülsheger, Alberts, Feinholdt, & Lang, 2013). Moreover, individuals who are depressed often utilize suppression-based techniques to regulate their emotions, which are typically ineffective in managing negative affect in the long term (Ehring, Tuschen-Caffier, Schnülle, Fischer, & Gross, 2010)(Fischer, & Gross, 2010; Gross & John, 2003). There is a correlation between intensified symptoms of depression and the utilization of suppression-based emotion management techniques like surface acting, which results in emotional dissonance. Emotional exhaustion follows emotional dissonance. Additionally, this study confirms that psychological resources are depleted and emotional exhaustion results when workers experience ostracism (Xia, Wang, Song, Zhang, & Qian 2019), (Jahanzeb, Fatima, & Malik, 2018), Given the impact of workplace ostracism on emotional exhaustion, it is advisable for managers to actively reduce or avoid instances of ostracism within the organizational setting. For example, organizations can reduce the instances of ostracism by encouraging face-to-face interactions among employees, improving employee well-being through diverse methods, fostering social engagement among employees, facilitating more communication avenues between colleagues, enhancing emotional expression and understanding, thus reducing the chances of ostracism. Additionally, research has shown that workplace ostracism depletes employees' emotional resources and leads to emotional exhaustion.

Secondly, the findings reject the H2 hypothesis, which claims that workplace ostracism has an adverse influence on employee engagement. Instead, they reveal that workplace exclusion has no positive influence on employee engagement. Employees who experience workplace ostracism are unable to demonstrate the anticipated level of job performance due to the diversion of their energy and time towards resolving interpersonal problems. Consequently, they are unable to access crucial job-related knowledge, resulting in reduced employee engagement. This phenomenon can shed light on the negative consequences that arise when employees perceive a lack of attention or inclusion from their colleagues or superiors. Such experiences tend to diminish their motivation and interest in their work, consequently impairing their productivity, overall job performance, and level of employee engagement. This study has the potential to assist firms in acknowledging the significance of establishing a working culture that promotes inclusivity. Employers may have a higher propensity to undertake measures aimed at minimizing workplace ostracism and fostering a work environment that is characterized by support and inclusivity. This may encompass the implementation of policies aimed at fostering diversity and inclusion, the provision of training programs for managers and employees to effectively recognize and treat instances of workplace ostracism, and the creation of opportunities for employees to engage and cooperate with their peers.

Thirdly, this study examines the role of emotional exhaustion in influencing employee engagement. The relationship between Employee Engagement and Emotional Exhaustion was found to be significant and negative, supporting the validity of hypothesis H3. Therefore, it is imperative for IT firms to prioritize the enhancement of employee engagement. Organizations have the potential to enhance employee engagement by utilizing various strategies such as role-playing, situational simulation, and alternative learning methods. These approaches facilitate effective communication among employees, foster understanding and recognition within the workplace, and mitigate the adverse effects of workplace ostracism thereby reducing emotional exhaustion. Furthermore, it is imperative for firms to actively seek out and hire individuals who possess advanced psychological abilities, and to foster an environment that promotes problem-solving through effective communication with colleagues. Ultimately, it is imperative for firms to prioritize the favourable effects of employee wellbeing. Organizations can promote productive communication, mutual assistance, and trust among coworkers through the implementation of teamwork initiatives. This approach facilitates the establishment of informal relationships, hence fostering the advancement of employee wellbeing. enterprise can choose to participate in team-building exercises such as exploration, team excursions, outward bound training, and team-based games to improve employee opportunities and well-being

Subsequently, employee well-being is the main concentrate of this study. The relationship between employee engagement and wellbeing was shown to be significant and positive, proving the validity of hypothesis H4. The relationship between the role of employee engagement on employee wellbeing is examined, taking into account the job, psychological, and personal well-being of employees. The mechanism by which negative workplace behaviors impact employee well-being is revealed by earlier study(L. Xing, Sun, & Jepsen, 2021), which also advances the profession's comprehension of this relationship (Panaccio & Vandenberghe, 2009). The provision of enhanced organizational support, including the positive atmosphere for communication and encouraging a positive organizational culture, is recommended for the organization. These measures are expected to facilitate the development of positive feelings among employees towards their work and aid in the restoration of resources necessary to counteract the adverse consequences of ostracism. Simultaneously, the firm has the potential to implement a psychological counselling mechanism for its personnel, aimed at decreasing emotional exhaustion and facilitating resource replenishment, with the ultimate goal of reducing negative emotions. In this particular context, an assessment has been conducted to examine the phenomenon of individuals who experience workplace ostracism, revealing that they tend to acquire resilience towards this adverse circumstance and ultimately exhibit enhanced psychological strength throughout their careers. Consequently, individuals who exhibit higher levels of employee engagement are likely to achieve greater success in their professional roles due to their enhanced creativity, enhanced ability to adapt to changes, and have the power to cope with difficulties.

Limitations and Future Research

This study acknowledges several limitations. Firstly, it focuses solely on IT companies in Southern India, potentially limiting the generalizability of its findings. Future studies could enhance the analysis by incorporating data from other states in Southern India to better understand the relationships between the variables. Additionally, the study exclusively involves IT professionals, suggesting the need to broaden the participant pool to include professionals from diverse sectors in future research efforts.

Moreover, the cultural context of the IT sector in Southern India may differ from that of other regions, affecting the study's applicability to broader populations. Furthermore, data collection occurred only at a single time point, highlighting the potential benefits of conducting longitudinal studies in the future. Lastly, the study relied solely on survey responses, limiting the depth of information obtained. Future research could benefit from incorporating in-depth interviews with participants to gain richer insights.

Despite these limitations, this study offers a valuable starting point for exploring workplace ostracism across various industries. It is recommended that future research consider moderating variables to further elucidate the detrimental effects of workplace ostracism. Additionally, expanding the participant pool to include individuals from non-profit institutions such as universities, hospitals, and schools would provide a more comprehensive understanding of this phenomenon.

References

Ashkanasy, N. M., Ayoko, O. B., & Jehn, K. A. (2014). Understanding the physical environment of work and employee behavior: An affective events perspective. *Journal of organizational behavior, 35*(8), 1169-1184.

Bakker, A. B., Schaufeli, W. B., Leiter, M. P., & Taris, T. W. (2008). Work engagement: An emerging concept in occupational health psychology. *Work & Stress, 22*(3), 187-200.

Boswell, W. R., Olson-Buchanan, J. B., & LePine, M. A. (2004). Relations between stress and work outcomes: The role of felt challenge, job control, and psychological strain. *Journal of Vocational Behavior, 64*(1), 165-181.

Chen, Y., & Li, S. (2020). Relationship between workplace ostracism and unsafe behaviors: The mediating effect of psychological detachment and emotional exhaustion. *Psychological reports, 123*(2), 488-516.

Chung, Y. W., & Yang, J. Y. (2017). The mediating effects of organization-based self-esteem for the relationship between workplace ostracism and workplace behaviors. *Baltic Journal of Management, 12*(2), 255-270.

Diener, E. (1984). Subjective well-being. *Psychological bulletin, 95*(3), 542.

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American psychologist, 55*(1), 34.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological bulletin, 125*(2), 276.

Ehring, T., Tuschen-Caffier, B., Schnülle, J., Fischer, S., & Gross, J. J. (2010). Emotion regulation and vulnerability to depression: spontaneous versus instructed use of emotion suppression and reappraisal. *Emotion, 10*(4), 563.

Fatima, A. (2016). Impact of workplace ostracism on counter productive work behaviors: Mediating role of job satisfaction. *Abasyn Journal of Social Sciences, 9*(2), 388-408.

Ferris, D. L., Brown, D. J., Berry, J. W., & Lian, H. (2008). The development and validation of the Workplace Ostracism Scale. *Journal of applied psychology, 93*(6), 1348.

Ferris, D. L., Lian, H., Brown, D. J., & Morrison, R. (2015). Ostracism, self-esteem, and job performance: When do we self-verify and when do we self-enhance? *Academy of management journal, 58*(1), 279-297.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50.

Glasø, L., Bele, E., Nielsen, M. B., & Einarsen, S. (2011). Bus drivers' exposure to bullying at work: An occupation-specific approach. *Scandinavian journal of psychology, 52*(5), 484-493.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. (2010). Multivariate Data Analysis: Pearson Education. *Upper Saddle River, New Jersey*.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., Ray, S., . . . Sarstedt, M. (2021). An introduction to structural equation modeling. *Partial least squares structural equation modeling (PLS-SEM) using R: a workbook*, 1-29.

Halbesleben, J. R., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR" understanding the role of resources in conservation of resources theory. *Journal of management, 40*(5), 1334-1364.

Heaphy, E. D., & Dutton, J. E. (2008). Positive social interactions and the human body at work: Linking organizations and physiology. *Academy of management review, 33*(1), 137-162.

Hitlan, R. T., Cliffton, R. J., & DeSoto, M. C. (2006). Perceived exclusion in the workplace: The moderating effects of gender on work-related attitudes and psychological health. *North American Journal of Psychology, 8*(2), 217-236.

Hobfoll, S. E. (2001). The influence of culture, community, and the nested-self in the stress process: Advancing conservation of resources theory. *Applied psychology, 50*(3), 337-421.

Howard, M. C., Cogswell, J. E., & Smith, M. B. (2020). The antecedents and outcomes of workplace ostracism: A meta-analysis. *Journal of applied psychology, 105*(6), 577.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal, 20*(2), 195-204.

Hülsheger, U. R., Alberts, H. J., Feinholdt, A., & Lang, J. W. (2013). Benefits of mindfulness at work: the role of mindfulness in emotion regulation, emotional exhaustion, and job satisfaction. *Journal of applied psychology, 98*(2), 310.

Ilies, R., Schwind, K. M., & Heller, D. (2007). Employee well-being: A multilevel model linking work and nonwork domains. *European Journal of Work and Organizational Psychology, 16*(3), 326-341.

Imran, M. K., Fatima, T., Sarwar, A., & Iqbal, S. M. J. (2023). Will I speak up or remain silent? Workplace ostracism and employee performance based on self-control perspective. *The Journal of Social Psychology, 163*(1), 107-125.

Jackson, S. E., Schwab, R. L., & Schuler, R. S. (1986). Toward an understanding of the burnout phenomenon. *Journal of applied psychology, 71*(4), 630.

Jahanzeb, S., & Fatima, T. (2018). How workplace ostracism influences interpersonal deviance: The mediating role of defensive silence and emotional exhaustion. *Journal of Business and Psychology, 33*(6), 779-791.

Jahanzeb, S., Fatima, T., & Malik, M. (2018). Supervisor ostracism and defensive silence: a differential needs approach. *European Journal of Work and Organizational Psychology, 27*, 430-440.

Jiang, Y., & Poon, K.-T. (2023). Stuck in companionless days, end up in sleepless nights: relationships between ostracism, rumination, insomnia, and subjective well-being. *Current Psychology, 42*(1), 571-578.

Kausto, J., Elo, A.-L., Lipponen, J., & Elovainio, M. (2005). Moderating effects of job insecurity in the relationships between procedural justice and employee well-being: Gender differences. *European Journal of Work and Organizational Psychology, 14*(4), 431-452.

Leung, A. S., Wu, L., Chen, Y., & Young, M. N. (2011). The impact of workplace ostracism in service organizations. *International Journal of Hospitality Management, 30*(4), 836-844.

Liu, H., & Xia, H. (2016). Workplace ostracism: A review and directions for future research. *Journal of Human Resource and Sustainability Studies, 4*(3), 197-201.

Lu, L., Gilmour, R., Kao, S. F., & Huang, M. T. (2006). A cross-cultural study of work/family demands, work/family conflict and wellbeing: the Taiwanese vs British. *Career Development International, 11*(1), 9-27.

Lyubomirsky, S. (2001). Why are some people happier than others? The role of cognitive and motivational processes in well-being. *American psychologist, 56*(3), 239.

Maslach, C., & Jackson, S. E. (1981). The measurement of experienced burnout. *Journal of organizational behavior, 2*(2), 99-113.

Mauno, S., Kinnunen, U., & Ruokolainen, M. (2007). Job demands and resources as antecedents of work engagement: A longitudinal study. *Journal of Vocational Behavior, 70*(1), 149-171.

Nagtegaal, I. D., & Quirke, P. (2008). What is the role for the circumferential margin in the modern treatment of rectal cancer? *Journal of Clinical Oncology, 26*(2), 303-312.

Nielsen, M. B., & Einarsen, S. (2012). Outcomes of exposure to workplace bullying: A meta-analytic review. *Work & Stress, 26*(4), 309-332.

O'Reilly, J., Robinson, S. L., Berdahl, J. L., & Banki, S. (2015). Is negative attention better than no attention? The comparative effects of ostracism and harassment at work. *Organization Science, 26*(3), 774-793.

Panaccio, A., & Vandenberghe, C. (2009). Perceived organizational support, organizational commitment and psychological well-being: A longitudinal study. *Journal of Vocational Behavior, 75*(2), 224-236.

Perrin, T. (2003). Working today: Understanding what drives employee engagement.

Reio Jr, T. G., & Sanders-Reio, J. (2011). Thinking about workplace engagement: Does supervisor and coworker incivility really matter? *Advances in Developing Human Resources, 13*(4), 462-478.

Riva, P., Wirth, J. H., & Williams, K. D. (2011). The consequences of pain: The social and physical pain overlap on psychological responses. *European Journal of Social Psychology, 41*(6), 681-687.

Robinson, S. L., O'Reilly, J., & Wang, W. (2013). Invisible at work: An integrated model of workplace ostracism. *Journal of management, 39*(1), 203-231.

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual review of psychology, 52*(1), 141-166.

Siegrist, J., Wahrendorf, M., Von Dem Knesebeck, O., Jürges, H., & Börsch-Supan, A. (2007). Quality of work, well-being, and intended early retirement of older employees – baseline results from the SHARE Study. *The European Journal of Public Health, 17*(1), 62-68.

Sommer, K. L., Williams, K. D., Ciarocco, N. J., & Baumeister, R. F. (2001). When silence speaks louder than words: Explorations into the intrapsychic and interpersonal consequences of social ostracism. *Basic and Applied Social Psychology, 23*(4), 225-243.

Spreitzer, G., & Porath, C. (2012). Creating sustainable performance. *Harvard business review, 90*(1), 92-99.

Sun, L. Y., & Pan, W. (2008). HR practices perceptions, emotional exhaustion, and work outcomes: A conservation-of-resources theory in the Chinese context. *Human resource development quarterly, 19*(1), 55-74.

Vale, F. (2011). *A Measurement of Employee Engagement Using the Gallup Q12 Workplace Audit.* Dublin, National College of Ireland.

Vanhala, S., & Tuomi, K. (2006). HRM, company performance and employee well-being. *management revue*, 241-255.

Warr, P. (1987). *Work, unemployment, and mental health*: Oxford University Press.

Watkins, M. B., Ren, R., Umphress, E. E., Boswell, W. R., Triana, M. d. C., & Zardkoohi, A. (2015). Compassion organizing: Employees' satisfaction with corporate philanthropic disaster response and reduced job strain. *Journal of Occupational and Organizational Psychology, 88*(2), 436-458.

Weiss, H. M., & Cropanzano, R. (1996). Affective events theory. *Research in organizational behavior, 18*(1), 1-74.

Whitman, M. V., Halbesleben, J. R., & Holmes IV, O. (2014). Abusive supervision and feedback avoidance: The mediating role of emotional exhaustion. *Journal of organizational behavior, 35*(1), 38-53.

Williams, K. D., Bernieri, F. J., Faulkner, S. L., Gada-Jain, N., & Grahe, J. E. (2000). The scarlet letter study: Five days of social ostracism. *Journal of Personal & Interpersonal Loss, 5*(1), 19-63.

Wright, T. A., & Bonett, D. G. (1997). The contribution of burnout to work performance. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 18*(5), 491-499.

Wright, T. A., & Cropanzano, R. (1998). Emotional exhaustion as a predictor of job performance and voluntary turnover. *Journal of applied psychology, 83*(3), 486.

Wu, L. Z., Yim, F. H. k., Kwan, H. K., & Zhang, X. (2012). Coping with workplace ostracism: The roles of ingratiation and political skill in employee psychological distress. *Journal of management studies, 49*(1), 178-199.

Xia, A., Wang, B., Song , B., Zhang, W., & Qian, J. (2019). How and when workplace ostracism influences task performance: through the lens of conservation of resource theory. *Human Resource Management, 29*, 353-370.

Xing, L., Sun, J. m., & Jepsen, D. (2021). Feeling shame in the workplace: examining negative feedback as an antecedent and performance and well-being as consequences. *Journal of organizational behavior, 42*(9), 1244-1260.

Xing, Y., & Yongzhou , L. (2022). How does workplace ostracism affect employee innovation behavior: An analysis of chain mediating effect. *Frontiers in Psychology*, 1-16.

Zheng, X., Zhu, W., Zhao, H., & Zhang, C. (2015). Employee well-being in organizations: Theoretical model, scale development, and cross-cultural validation. *Journal of organizational behavior, 36*(5), 621-644.

Zhu, H., Lyu, Y., Deng, X., & Ye, Y. (2017). Workplace ostracism and proactive customer service performance: A conservation of resources perspective. *International Journal of Hospitality Management, 64*, 62-72.

Zippelius, R. (1986). Exclusion and shunning as legal and social sanctions. *Ethology and Sociobiology, 7*(3-4), 159-166.

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Capturing Netizens' Sentiment of Electric Cars through Twitter Using NVivo

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Abstract

One of the main strategies for lowering greenhouse gas emissions from the transportation industry is the employment of modern, energy-efficient, sustainable mobility technology, such as electric vehicles. Despite the financial and non-financial incentives offered to customers and manufacturers worldwide, the acceptance and adoption of electric cars are still relatively low, and persuading customers to use EVs has proven challenging. To ascertain how people generally feel about the category of electric cars, the current study attempts to do sentiment analysis. 15320 tweets were recorded with the help of NCapture, based on a specific hashtag, "electric car" between the timeframe of 1st to the 30th of May in 2023. NVivo software was used to analyse the data. The study reveals that Twitter users generally have positive attitudes towards electric cars, outnumbering negative ones. It provides recommendations for governmental organizations, private firms, legislators, and other stakeholders to better serve the general population's needs.

Keywords: Electric Cars, Negative, NVivo, Positive, Sentiment Analysis, Social Media; Twitter Data

Introduction

In today's world of ecological imbalances caused by enterprises' excessive carbon emissions into the atmosphere, constructing a green economy is critical. Degradation of the environment not only lowers productivity but also destroys the economy as a whole. The greenhouse gases emitted by anthropogenic activities, such as using fossil fuels for energy generation, cause environmental deterioration and climate change. Globally, the

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Sustainable Development Goals (SDGs) and Climate Agreements encourage firms to go green by lowering their carbon impact (Ellahi et al., 2021).

The likelihood of environmental degradation could increase with increased reliance on energy-intensive transportation systems. The transportation industry globally produced 7.29 billion metric tons of CO_2 ($GtCO_2$) in 2020 and was the second-largest carbon dioxide emitter (European Commission). Switching from conventional to energy-efficient vehicles such as electric cars is a practical technique for reducing the rate of carbon emissions. The essential advantage of an electric car is that it emits fewer pollutants, lessening detrimental environmental effects. It decreases air quality and human health dangers and reduces greenhouse gas emissions. They also aid in the improvement of the energy security position of the world. While new car fuel economy improves yearly, an electric car is considered even more environmentally beneficial than gasoline or diesel-powered vehicles since it runs on electricity.

Electric cars, which do not require gasoline or diesel, rose to prominence in 1973 when the oil crisis sparked increased interest in alternate fuel sources. By the late 1990s, alternative-fuel vehicles were being displayed as concept cars at car events worldwide. Automobile manufacturers intended to demonstrate to buyers what types of automobiles they could buy in the following years and how they would save money on gas. These vehicles also had a "green" advantage, as a vehicle that uses less petroleum than a regular car emits fewer pollutants into the atmosphere.

Comparing Conventional Cars and Electric Cars

Internal combustion engines running on fossil fuels, used in traditional cars, release greenhouse gases and other air pollutants. In contrast, electric cars use electricity stored in batteries and emit no emissions through the exhaust pipe. At the same time, the overall environmental impact relies on the method used to generate electricity. Compared to the waste heat generated by internal combustion engines, electric cars typically turn a higher percentage of the stored energy into usable work. However, electric vehicles typically only have a short driving range on a single charge and require a still-evolving charging infrastructure. Additionally, unlike the complex engines of traditional automobiles that necessitate routine maintenance, electric cars have fewer moving parts and frequently require less maintenance, even though the battery pack's performance and lifespan may degrade with time (Basu et al., 2019; Bauer et al., 2015; Denholm & Short, 2006; Hawkins et al., 2013). The detailed comparison between conventional cars and electric cars is depicted in Table-1.

Table-1: Conventional Cars v/s Electric Cars

Aspect	Conventional Cars	Electric Cars
Fuel Source	Fossil fuels (gasoline, diesel)	Electricity stored in batteries
Emissions	Greenhouse gases, air pollutants	Zero tailpipe emissions
Energy Efficiency	Relatively low efficiency due to waste heat	Higher efficiency, converting more energy from the battery into practical work
Range and Charging Infrastructure	Longer driving range, established refueling	Limited range on a single charge, need for charging infrastructure
Maintenance and Battery Life	Regular maintenance, wear, and tear on components	Fewer moving parts, reduced maintenance needs, battery degradation over time

The electric vehicle market is growing steadily around the world. However, the adoption environment-friendly electric cars are still relatively low globally, therefore studying the public's sentiments toward electric cars is essential. Social media is a rich source of textual information that makes it possible to accurately analyze and understand public opinion. Public opinion in most countries recognizes the significance of climate change, even though perceptions of the environmental effects of car use are likely to vary from country to country. The public is perceived as having the power to alter outcomes by their behaviors if they become aware of the significance of environmental degradation, their influence on other people, species, and the world, and their responsibility for environmental concerns (Walker & Spurgeon, 2003).

The study's primary objective is to understand customer sentiments, attitudes, anxieties, and acceptance of electric vehicles. Because consumer opinions are freely stated on social media sites, the Internet has enormous potential to deliver information on these opinions. Businesses can learn more about how consumers perceive a product by examining various social media platforms.

Sentiment Analysis

Sentiment analysis can identify customer impression of a product, public opinion, and other factors by utilizing text analysis methods to "understand and classify emotions (positive, negative, and neutral) inside text data." Businesses can use sentiment analysis tools to determine customer sentiment about products, services, or brands based on internet comments (Sainger, 2021). Media communication influences strategy, decision-making, and leadership. The socialization hypothesis also highlights how people's communication influences their cognitive, affective, and behavioral views (Sainger, 2021). It eliminates subjective judgments and personal biases while providing a comprehensive and rigorous technique for assessing data in this innovative and difficult field. Sentiment analysis, when properly integrated into current decision-making methodologies, has the potential to change the decision-making process.

Facebook, Twitter, and Instagram are among the most popular social media platforms, where people like sharing their experiences, stories, lifestyles, and hobbies. Twitter had 187 million users worldwide in 2021. The study provides significant literary contributions. First and foremost, the use of QSR NVivo 14 software will enable groundbreaking study into public sentiments on social media, particularly Twitter. Second, it provides relevant data for policymakers to use in promoting the use of electric vehicles. Third, it drives corporate decisions to provide them with a competitive advantage.

The structure of this study is as follows. Literature relevant to the study is provided in section 2. The data and research methodology utilized in the study are explained in Section 3. Analysis of the paper's primary results is presented in Section 4. Finally, a conclusion and discussion draw in Section 5.

Review of Literature

Sentiment analysis is a technique for identifying and extracting sentiment conveyed in text, such as social media posts, reviews, or news reports. Sentiment analysis seeks to evaluate whether a text's sentiment is positive, negative, or neutral. The study's authors extract and summarize sentiment transmitted in social media conversations utilizing contextual and conceptual sentiment analysis approaches. This work used NVivo 14 for sentiment analysis. There have been studies that used various methodologies to investigate public opinion on social media. Some of the previous works on sentiment analysis are given below.

Wulandari (2023) investigated the elements influencing Generation Z's intention to buy electric cars (EVs) in Jakarta. The open-ended qualitative questionnaire revealed Generation Z's intentions to buy EVs, their awareness of and worry over environmental problems associated with EVs, and their opinions of marketing initiatives from businesses and government initiatives. The sentiment analysis from Twitter found favourable sentiment favorable electric vehicles, including the Hyundai Ioniq 5, Wuling Air EVs, electric motorcycles, and electric cars.

Alhari et al. (2022) used the Support Vector Machine method to classify tweets and identify favorable and unfavorable sentiments about the deployment of electric vehicles in Indonesia. They obtained datasets pertaining to their research topic from the social networking website Twitter. The 1502 Tweet opinions in the analyzed data set had a 79% positive sentiment classification distribution and a 21% negative sentiment classification distribution for electric cars in Indonesia.

Demirer & Büyükeke(2022) conducted research to investigate consumer impressions of the TOGG electric vehicle, which had recently been released in Turkey at the time. The authors used the Twint Crawler API to collect data from December 2019 to February 15, 2021, primarily from Tweets on the social media app Twitter. The authors then analyzed the acquired data using a range of methodologies, including Logistic Regression and an LDA model from the Gensim Library. The study's findings revealed that the general population had a favorable perception of the TOGG car.

Suresha & Kumar Tiwari (2021) used the Twitter API to collect user tweets regarding electric vehicles and then analyzed how the general public perceived them. They used a natural language processing (NLP) algorithm to choose tweets after collecting the data. They investigated numerous aspects of electric vehicles using a variety of topics, such as modeling, word clouds, and EDA. Then, "sEntiment Reasoner (SONAR)" and "Valence Aware Dictionary (VADER)" are utilized to examine the sentiment of electric vehicles. The findings revealed that the most popular hashtag shared on Twitter was #Tesla. The majority of users were found in Sweden, specifically Ekero. According to VADER, 47.1% of tweets are favorable, 42.4% are neutral, and 10.5% are unfavorable.

Handayani & Mustikasari(2020) set out to evaluate the accuracy of models built using tweets with positive, negative, and neutral sentiments. Tweet Scrapper was used in the study to collect Tweets. When used to classify the sentiment of tweets in Indonesian, the models were developed using the recurrent neural network. From the studies, Twitter using the RNN approach utilizing the Confusion Matrix produced the best test results, with a Precision 0.618, Recall 0.507, and Accuracy 0.722 on the data amounting to 3000 and a comparative data training and data testing of 80:20.

(Saura et al., 2019) The study's objectives were to pinpoint the crucial User Generated Content (UGC) on the social media platform Twitter for developing prosperous businesses and to pinpoint elements for sustainable startups and business strategies. The authors determined the database topic using the Latent Dirichlet Allocation (LDA) model, a theme modeling method that runs in Python. Then, sentiment analysis was carried out using Python's Supervised Vector Machine (SVM) approach for machine learning. Based on the LDA categorization. This was used to categorize the identified startup subjects into negative, positive, and neutral feelings. The subjects in each sentiment were then subjected to Textual Analysis utilizing NVivo software and Text Data Mining techniques.

Asare et al. (2021) sought to examine how the general public felt about emergency remote learning (ERL) during COVID-19, from 10 March 2020 to 24 July 2020. Using the Twitter API, 31,009 Tweets were obtained for the study. The data was cleaned using Python libraries and NVivo, and gathered tweets were examined using word frequencies of bigrams and unigrams, sentiment analysis, topic modeling, sentiment labeling, cluster analysis, and trend analysis. In the dataset and identified themes, the results revealed mixed sentiments.

Septia Irawan et al. (2022) studied to comprehend the public debate on the front-of-pack nutrition labeling (FOPL) system in the European Union (EU) by examining tweet content, sentiment, and mapping network characteristics. Tweets were searched for without regard to time or language, and data was gathered using the Twitter application programming interface (API). Using the QRS NVivo software, the content was coded and thematically examined. Network analysis was done with Gephi 0.9.2, and automatic sentiment analysis was done with QSR NVivo. The findings indicated that the UK, Spain, and France were the central posting countries for tweets. The discussion on Twitter has given rise to several themes, including different types of food labeling, the food industry, the distinction between healthy and unhealthy foods regarding food labeling, EU regulation, political strife, and science and education. On Twitter, the conversation was dominated by Nutri-Score.

Reyes-Menendez, et al. (2018) determined vital indicators relating to hotel sustainability and environmental management as perceived by hotel visitors. An algorithm created in Python and trained with data mining and machine learning using the MonkeyLearn library was utilized for sentiment analysis of the hotel industry sector using the eWOM (e-Word of Mouth) model. The qualitative analysis program vivo Pro 12 was used to conduct a textual analysis of the outcomes with negative, positive, and neutral feelings.

Palos-Sanchez, et al. (2018) sought to discover the positive, neutral, and negative environmental aspects that impact visitors to Spanish hotels to assist the hotel management in determining how to raise the caliber of the services offered. In order to conduct the study, a Sentiment Analysis was first conducted, grouping the sample of 14459 tweets according to the emotions expressed. Next, a textual analysis was conducted using the qualitative analysis software NVivo (QSR International, Melbourne, Australia) to identify the critical environmental factors in these emotions. The findings highlight the critical environmental elements influencing visitors' experiences at Spanish hotels, including preserving rural areas' natural beauty and respect for local traditions and products, air quality protection in areas where hotels operate facilities and provide services, and more.

Reyes-Menendez et al. (2018) pinpointed the social, economic, environmental, and cultural aspects of sustainable environmental and public health care that Twitter users are most concerned about. The tweets were then subjected to sentiment analysis by the authors, who subsequently categorized them according to the emotions conveyed. The Sustainable Development Goals (SDGs) were then utilized to group the tweets, and a textual analysis was conducted to determine the main environmental and public health issues that Twitter users are most concerned about. NVivo Pro 12 was utilized as the qualitative analysis program for this.

Research Methodology

The method to conduct the study is qualitative with social media sentiment. Qualitative research has the advantage of allowing for an in-depth examination of complex, diverse situations. It enables researchers to record the variety and richness of individuals' experiences and comprehend the meaning that those experiences have for those people. The tool QSR NVIVO 14 is used for analysis of tweets from Twitter. Examining unstructured data from social networking websites can be beneficial with this program. NVivo, a program that automatically analyses sentiment, is based on sentimental expressions in the content. NVivo's qualitative analysis has been frequently used to examine reviews, social media posts, and interview data, increasing their reliability by removing bias.

People frequently use Twitter as a social media platform to express their opinions and sentiments regarding goods and services (Suresha & Kumar Tiwari, 2021). Many researchers have collected data from this platform to analyze sentiments on a variety of social topics because of the number of shared perspectives there (Asare et al., 2021; Bauer et al., 2015; Saura et al., 2018, 2019; Septia Irawan et al., 2022). Using the aid of NCapture, we went on to gather tweets that were tagged with the hashtag #electric car between May 1 and May 30 of the year 2023. Within this predetermined period, 15320 tweets, including retweets, were posted, making up our sample size. NVivo was used to import the dataset and conduct sentiment and further analysis.

Sentiment analysis seeks to ascertain whether people have positive, negative, or neutral feelings or thoughts about a good, service, or information. This is quite helpful for getting a broader public perspective on specific topics on social networking sites like Facebook, Twitter, and WhatsApp Groups, among others. Due to the availability of real-time scenarios like people's opinions and feelings, etc., the decision-making process is now quicker and easier than it was in the past (Sainger, 2021). This study used computer-assisted analysis to improve comprehension of each tweet's content. Following sentiment-based categorization of the tweets, auto coding is used, with codes clustered by word similarity indicating logical groups. After studying groups, NVivo's auto-coding feature successfully divided the tweets into categories according to their positive, negative, or neutral emotional analysis.

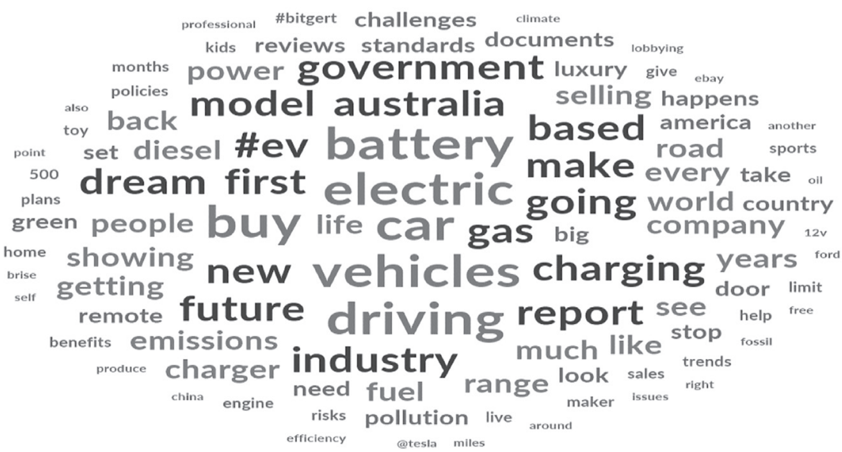
Results

Word Frequency Analysis

Figure-1 shows the word cloud created from the tweets. Word clouds are visual representations that demonstrate how frequently certain words appear. A NVivo's auto-coding feature successfully divided the tweets into categories according to their positive, negative, or neutral emotional analysis. A word's magnification in the final image is proportionate to how often it appears in the examined text.

Tweets typically contain the words "car," "electric," "vehicles," "driving," and "battery." These terms have a direct relationship to the idea of electric cars. Since electric cars require charging and are one type of electric vehicle (EV), the terms "charging," "ev," and "future" refer to the characteristics of electric cars. According to this vision, electric cars are the way of the future of mobility. Since gasoline-powered cars will be replaced by electric cars, these cars are constantly contrasted with one another. The words "gas" and "charging" from the analysis of the word cloud created from tweets highlight this resemblance. As the government supports the electric vehicle market and offers incentives to consumers to buy green cars. Therefore, the words "government" and "industry" in dominated words also show how the government supports and regulates the economy.

Figure-1: Word Cloud



Key sentiments as per word cloud: Following are the key sentiments on the basis of manual content analysis of the tweets as per the word cloud:

- **Overall Tone:** The inclusion of both positive ("future," "green," "benefits") and potentially negative phrases ("challenges," "issues," "risks") indicates a mixed attitude of tweeter users toward electric vehicles. The positive phrases convey optimism and the potential benefits of electric vehicles, whilst the negative terms emphasize the hurdles and hazards that must be overcome for them to reach their full potential. This range of emotions represents a balanced outlook on the future of electric vehicles.

- **Excitement and Optimism:** The focus on "future," "emissions," and "green" suggests that people may be excited about the environmental and technological breakthroughs linked with electric vehicles. The excitement and hope surrounding electric vehicles stem from their promise to transform the automobile industry, cut carbon emissions, and create a more sustainable future.
- **Concerns and Skepticism:** Words like "challenges," "range," and "charging" underline practical aspects of electric vehicle adoption, such as infrastructure and battery life. However, worries regarding infrastructure, battery life, and cost indicate that considerable barriers must be overcome before electric vehicles can become ubiquitous. Overall, the disparities in attitudes regarding electric vehicles reflect a complicated and changing picture in the automobile sector. As technology advances, electric vehicles are set to play an increasingly crucial part in the future of transportation.
- **Consumer Interest:** The inclusion of "buy," "reviews," "government," and "needs" implies that individuals are seriously investigating electric vehicles, evaluating the benefits against the potential negatives. This implies that as more information becomes available and electric vehicle technology advances, consumer interest and adoption rates may continue to climb. Furthermore, government incentives and laws aimed at encouraging sustainable transportation could have a big impact on the future adoption of electric vehicles.
- **Global Relevance:** Words like "world," "China," and "Australia" indicate an interest in the worldwide effect and development of electric vehicles. This suggests a rising awareness of traditional automobiles' environmental impact, as well as a shift toward more sustainable modes of transportation. As countries throughout the world like Australia and China try to reduce carbon emissions, electric vehicles are expected to become increasingly popular among customers.

Sentiment Analysis

The sentiment analysis of the 15320 tweets about electric cars was conducted using NVivo-14. The sentiment analysis results reveal a combination of positive and negative sentiments, which indicates a neutral sentiment overall. The bulk of tweets falls into the moderately negative and moderately positive categories, indicating that tweets express both optimistic and pessimistic views about electric cars.

The information in Table-2 reveals that, with a total of 897 tweets, the "Moderately positive" emotion group has the highest tweet volume. The advantages of electric cars over traditional gasoline-powered ones include their incredible environmental friendliness, affordability as their costs is beginning to catch up with those of conventional cars, and availability of several features not found in conventional cars, such as instant torque and regenerative braking. The sentiment categories of "Moderately negative," "Very negative," and "Very positive" were analyzed for tweets about electric cars. 840 tweets in the "Moderately negative" category expressed worries, complaints, and risks associated with the deployment of electric cars. Because they are more expensive to buy and operate than conventional cars, have a limited range, and lack a charging infrastructure in some places. 461 tweets in the "Very negative" category were critical of electric vehicles. The lowest number of tweets, 299, fell into the "Very positive" category. Overall, there was a reasonable amount of hostility and positivity towards electric cars on Twitter over the studied period. The analyzed tweets contain pessimists and optimists of electric cars, with proponents and optimists being more common.

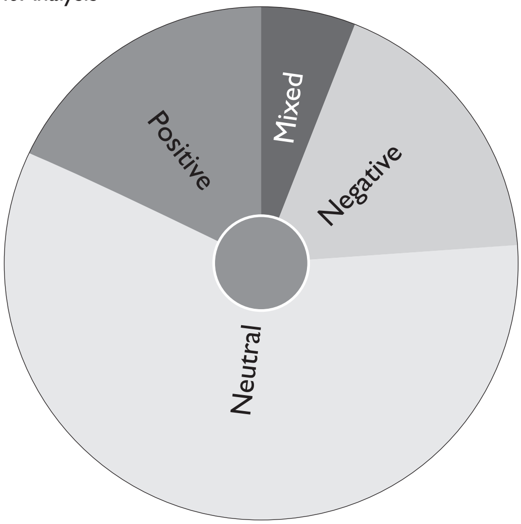
Table-2: Sentiment Toward Electric Cars

	Sentiment Analysis
1: Very negative	461
2: Moderately negative	840
3: Moderately positive	897
4: Very positive	299

Positive vs. negative sentiment

The dataset's positive vs. negative sentiment is analyzed using the built-in scoring mechanism for auto-coding provided by NVivo (v14). Figure-2 shows the positive and negative sentiments from tweets on electric cars. The majority of tweets have a neutral tone. This is good news for the environment since more government laws and incentives will make it simpler for people to adopt the idea of electric cars. However, the public has a wrong impression of electric cars because they are expensive and have less infrastructural availability. The adoption of electric cars is still in its infancy; thus, governments and other national organizations should consider the likelihood that the current neutral attitude towards them will shortly shift towards a positive one. This calls for a thoroughly thought-out communication plan that emphasizes the advantages of this novel technology.

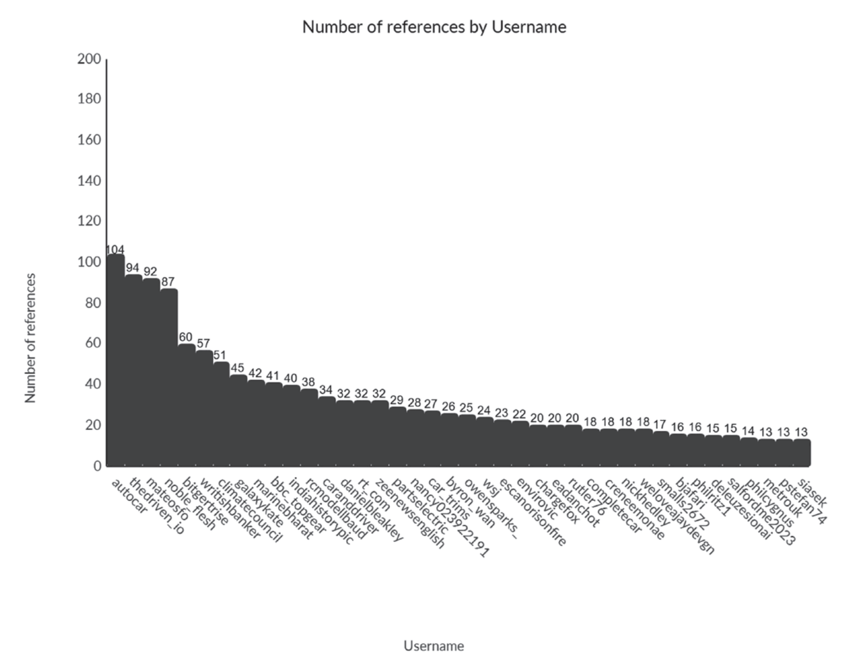
Figure-2: Sentiment Analysis



Number of References by Username

Figure-3 shows the usernames 'Autocar' and 'thedriven_io' have more references than the other usernames combined. Autocar is a British automobile publication published by Haymarket Motoring Publications Ltd., a branch of Haymarket Media Group. Haymarket Media Group is a British publishing company that produces periodicals, newspapers, websites, and events. Autocar is the world's oldest automobile publication. Autocar covers the automobile business in all aspects, including news, reviews, features, and opinion (Autocar, n.d.). The Driven is an Australian website that provides news and analysis on electric vehicles (EVs) and the zero-carbon transition. It presents a detailed and insightful review of the latest industry advancements and a diversity of opinions on the future of EVs (The Driven, n.d.). Apart from that, mateosfo, which ranks third in terms of the number of mentions, is the Twitter handle of Matthew Lewis, a proponent of progressive federalism. He frequently tweets about urban planning, public transportation, and climate change. He is also an outspoken opponent of car culture and suburban sprawl. Overall, these accounts likely have a significant focus on electric vehicles and may be considered industry leaders or news sources in this domain. This analysis also show that the number of tweets from general public at large are limited in comparison to news sources and leaders, who have higher number of mentions.

Figure-3: Number of References by Username

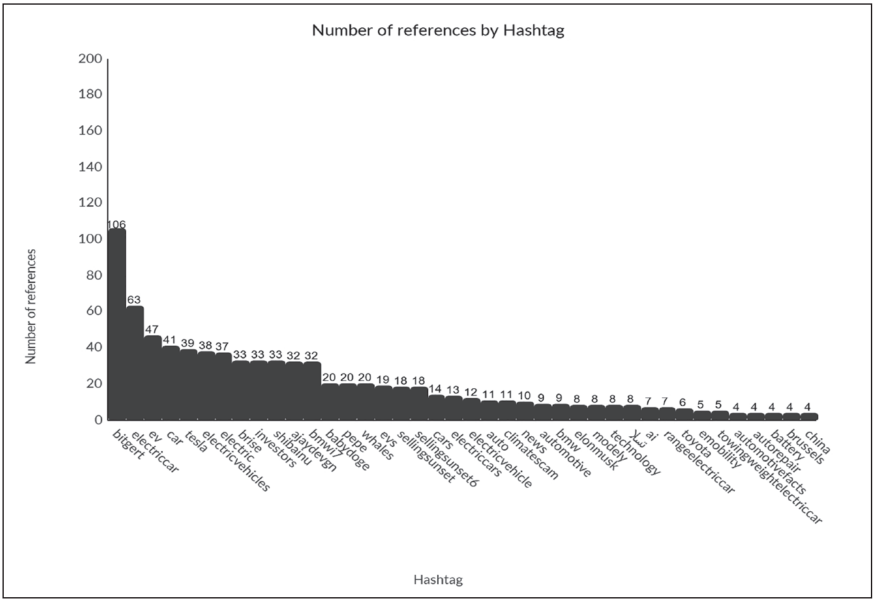


Number of References by Hashtag

Among the first five entries on the list, one hashtag relating to 'bitgert' has clearly outperformed 'electric car,' 'ev,' 'car,' and 'tesla' (Figure-4). Bitgert, a crypto engineering project specialising in blockchain products and auditing solutions, was founded in July 2021 and quickly gained traction and prominence when it announced the creation of the QBRISE electric automobile in March 2022. Bitgert is dedicated to making electric cars more accessible and inexpensive by developing its own QBRISE electric cars line and an electric car payment system based on blockchain technology. The link between Bitgert and electric cars is significant because it illustrates that Bitgert is more than just a cryptocurrency project; it is also a corporation that is concerned about the future of transportation (Bitgert - Fastest & Cheapest Blockchain, n.d.). The fifth entry, 'Tesla,' refers to Tesla, Inc., an American multinational automotive and energy company headquartered in Austin, Texas that designs and manufactures electric vehicles, stationary battery energy storage devices ranging from home to grid-scale, solar panels, solar roof tiles, and related products and services. Tesla's objective is to "accelerate the world's transition onto sustainable energy." The company has been a leading force in the development of the electric car sector, and its products have been lauded for their performance, range, and technology (Tesla, n.d.).

Furthermore, the hashtag 'brise' promotes Bitgert's aim to develop a payment system for electric vehicles that will allow users to pay for charging their vehicles using BRISE tokens and C+Charge (C+Charge, n.d.; Paybrise, n.d.). This payment mechanism will significantly advance the electric vehicle business, making electric vehicles more accessible and inexpensive to everybody. Furthermore, the tenth entry, 'Shibainu,' refers to Shiba Inu (SHIB), a decentralized cryptocurrency launched in August 2020 by an unidentified individual or group known as "Ryoshi." A group of SHIB holders wants to promote the usage of electric cars as a more environmentally friendly mode of transportation. Some SHIB holders have already begun using their SHIB to purchase electric cars, urging others to do the same (Shibtoken, n.d.).

Fig-4: Number of References by Hashtag

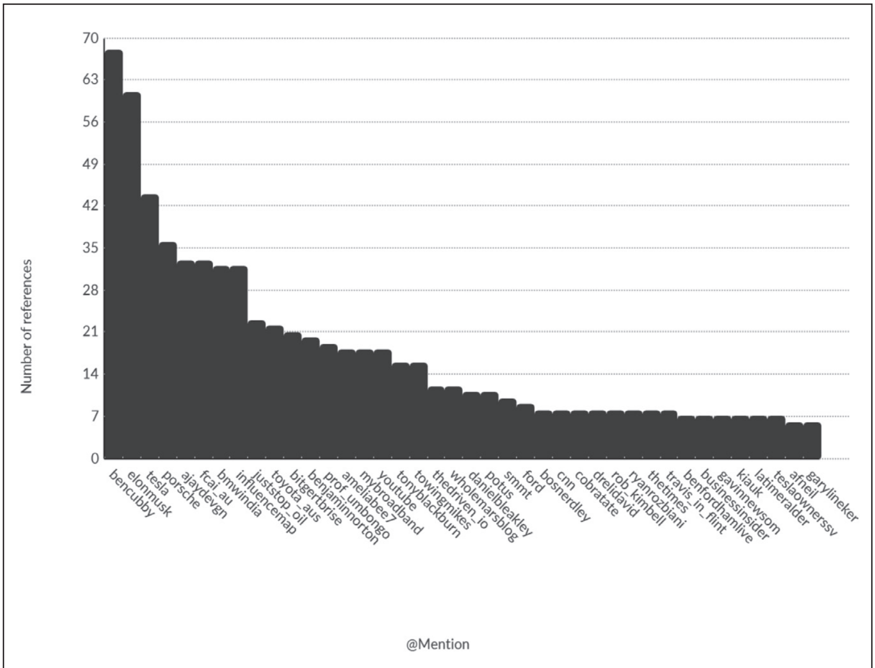


Number of References by @mention

Regarding mentions Figure-5 Ben Cubby and Elon Musk have received the most attention. Ben Cubby is a Sydney Morning Herald investigative reporter. (Ben Cubby | The Sydney Morning Herald, n.d.) The Sydney Morning Herald (SMH) is an Australian daily newspaper published in Sydney, New South Wales. Ben Cubby frequently posts headlines about electric vehicles and Australian governments' intentions to promote electric vehicles on Facebook, Twitter, and in his newspaper. People usually mention him when discussing the latest electric vehicle news.

According to the data, Ben outperforms Elon Musk, who is mentioned less frequently than Ben. Elon Musk is CEO of Tesla, the world's largest manufacturer of electric vehicles. Tesla has played a key role in the growth of the electric vehicle industry, and Musk is widely regarded as a visionary leader in the field. Musk is an enthusiastic proponent of electric automobiles. He has repeatedly tweeted about the benefits of electric vehicles, even challenging rival automakers to produce more of them. People are talking about Bollywood actor Ajay Devgn since he recently received a BMW i7, the brand's flagship electric car. Devgn tweeted a picture of himself with the car, which instantly went viral. Many people admired Devgn's choice of car and applauded him for supporting the electric car movement. Many people have been impressed by Devgn's choice to switch to an electric car, which has helped promote awareness of electric cars in India. Porsche and BMW have also been suggested numerous times. These automakers have a variety of high-performance electric cars on the market.

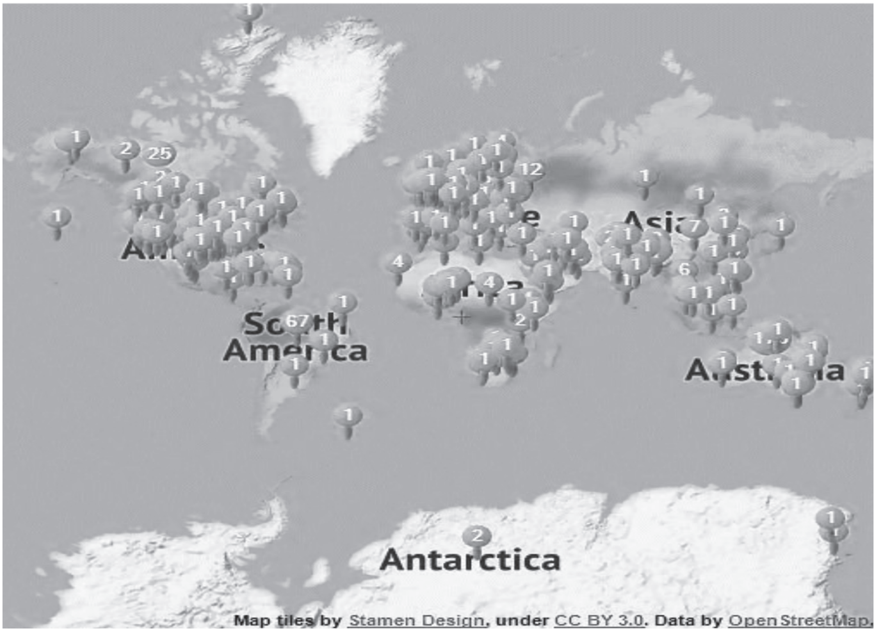
Figure-5: Number of References by @mention



Map

Figure-6 depicts the source of tweets about electric cars. It is critical to exercise caution because the accuracy of data origination may be jeopardized by using Virtual Private Networks (VPNs). Europe and North America regions have the highest degree of activity in terms of tweets about electric vehicles. Furthermore, Asian countries, particularly India, are engaged in significant activities. Most of these tweets come from metropolitan locations in India, such as Delhi, where people rapidly adopt electric vehicles due to government programs, incentives, and other policies. However, because of the widespread use of social media, the prevalence of tweets on any particular issue tends to be higher in developed countries.

Figure-6: Map



Twitter Sociogram

A Twitter sociogram is a graphical representation or investigation of the social network architecture and associations among Twitter users. This provides insight into how users communicate with one another, patterns of connections, and information transfer within the Twitter population. The analysis contains several options, such as retweeting and mentioning edges. As shown in Table-3, the output display includes size and vertices by degree, filter vertices by minimal degree, and scale edge weight by number of retweets and mentions. The three usernames with the most betweenness score, which shows the accounts with the most mentions and retweets, were discovered to be 'Chargefox' (betweenness = 624760.886), 'TheDriven_io' (betweenness = 607589.335), and 'Tesla' (betweenness = 505991.161). Here Chargefox is Australia's largest and fastest-growing electric vehicle (EV) charging network. It was established in 2017 to make charging simple, reasonable, and quick for all Australians. Chargefox's network spans Australia and has over 1,400 charging stations(Chargefox, n.d.). The Driven is an Australian website that covers news and analysis about electric vehicles (EVs) and the transition to zero carbon and sustainable transportation. Tesla, Inc., headquartered in Austin, Texas, is an American multinational automobile and energy corporation that designs and manufactures electric vehicles, stationary battery energy storage systems ranging from residential to grid-scale, solar panels, solar roof tiles, and related goods and services.

It indicates that these companies play a key role in the EV discourse on Twitter. The table also indicates that a variety of other users are interested in EVs, including journalists, experts, and enthusiasts. This shows that there is a significant and active community of EV enthusiasts on Twitter. Overall, the table provides an insightful glimpse of the EV discourse on Twitter. It demonstrates that there is a great deal of interest in electric vehicles and that several firms and organizations are leading the way in this discussion.

Table-3: Sociogram List - Top 30

Username	Degree	Degree In	Degree Out	Betweenness
Chargefox	19	19	0	624760.886
TheDriven_io	102	102	0	607589.335
Tesla	39	39	0	505991.161
elonmusk	58	58	0	413642.738
MikeeGipson	7	0	7	410085.482
Gill_Nowell	11	10	1	362594.666
SirianSto	3	0	3	359637.953
KateFantom	5	5	0	358937.455
autocar	79	79	0	341924.662
mateosfo	78	78	1	271636.000
stingertimj	9	0	9	259714.455
philrandal	2	0	2	259584.000
SinoAutoInsight	3	1	2	240821.432
TomRaftery	4	0	4	226360.348
HibbsA	2	1	1	220773.539
TomSesselmann	5	0	5	214000.792
JHandwerg	4	0	4	174738.893
Porsche	36	36	0	139838.399
CARandDRIVER	36	35	1	139838.399
FathiFrwinia	2	0	2	125744.000
bitgertbrise	22	22	0	125001.000
TravellingSouth	9	0	9	118007.411
another07047584	9	0	9	118007.411
zilspeed	8	0	8	115725.411
Assumpfarran	2	0	2	114726.439
EvelynSpring8	2	0	2	114726.439
climate_fact	10	0	10	108278.000
Cowloe	2	0	2	100832.000
GalaxyKate	46	46	0	100708.000
bencubby	66	66	0	94588.922

Discussion of Results

Electric vehicles are regarded as a significant game changer in the automotive sector worldwide, attracting the interest of academics and scientists from numerous fields. However, global adoption of environmentally friendly electric vehicles remains low, making it vital to examine consumer attitudes towards them. The study's primary purpose was to better understand customer attitudes, concerns, and acceptance of electric vehicles. To that purpose, the QSR NVIVO 14 tool was used to analyze public sentiments on social media, specifically Twitter. According to the statistics, the terms "car," "electric," "vehicles," "driving," and "battery" are frequently used in tweets. The mixture of both positive ("future," "green," "benefits") and potentially negative terms ("challenges," "issues," "risks") demonstrates twitter users' mixed feelings about electric vehicles.

According to sentiment research, tweets indicate both good and negative feelings on electric vehicles, with the majority falling into the moderately favorable and moderately negative category. The "Moderately positive" attitude category has the most tweets, with 897. The reasons for being positive about electric cars include the fact that they are a more environmentally friendly option than traditional gasoline-powered cars, that prices are beginning to fall in order to compete with traditional cars, and that they provide several features those traditional cars do not, such as instant torque and regenerative braking. The majority of the tweets are neutral in tone. This benefits the environment since the electric car concept can be quickly adopted with better government regulations and incentives.

Bitgert, Twitter's most popular hashtag, is a crypto engineering venture focused on blockchain products and auditing solutions. Bitgert is focused to making electric cars more accessible and affordable by building its own QBRISE electric car line and a blockchain-based payment system. The British motor journal 'Autocar' and the Australian website 'The Driven were the two users that posted the most Tweets with the hashtag #electric cars during the period. The names Ben Cubby and Elon Musk have been mentioned the most. Ben Cubby routinely posts articles on Facebook, Twitter, and in his newspaper 'The Sydney Morning Herald' regarding electric vehicles and the Australian government's initiatives to encourage electric automobiles. Moreover, Elon Musk is the CEO of Tesla, the world's leading electric car manufacturer. Tesla has been a driving force in the expansion of the field of electric cars.

Another finding from the above data is that people in developed nations are likelier to Tweet about electric cars. Europe and North America regions have the highest degree of activity in terms of tweets about electric vehicles. Furthermore, Asian countries, particularly India, are engaged in significant activities. Most of these tweets come from metropolitan locations in

India, such as Delhi, where people rapidly adopt electric cars due to government programs, incentives, and other laws. The Sociogram also found that the three usernames with the highest betweenness score, which shows the accounts with the most mentions and retweets, are 'Chargefox,' 'TheDriven_io, 'and 'Tesla.' Here, Chargefox is Australia's most extensive and rapidly expanding electric vehicle (EV) charging network. As a result, this study will assist and guide government agencies, individual organizations, policymakers, automobile companies, the general public, and other stakeholders in making more informed decisions on adopting electric cars.

Future Outlook

As this study focused solely on sentiment analysis via tweets, future studies could include posts and interactive discussions from other social media platforms to analyse broad public views. Furthermore, because the current study only looked at tweets from a short period, future researchers can conduct a longitudinal study by developing a real-time monitoring system that continuously analyses tweeter data related to electric cars and captures trends and sentiment shifts over time. Furthermore, it should be noted that the sentiment analysis results only reflect the public's attitude toward electric cars at a specific time. As the market for electric cars expands, public opinion may shift. Future studies could look into other parts of qualitative research of sentiment analysis and data mining, such as factors influencing the adoption of electric cars and thematic analysis.

References

Asare, A. O., Yap, R., Truong, N., & Sarpong, E. O. (2021). The pandemic semesters: Examining public opinion regarding online learning amidst COVID-19. *Journal of Computer Assisted Learning*, *37*(6), 1591-1605. https://doi.org/10.1111/jcal.12574

Basu, A. K., Tatiya, S., & Bhattacharya, S. (2019). Overview of Electric Vehicles (EVs) and EV Sensors. In *Energy, Environment, and Sustainability* (Issue January). Springer Singapore. https://doi.org/10.1007/978-981-13-3290-6_7

Bauer, C., Hofer, J., Althaus, H. J., Del Duce, A., & Simons, A. (2015). The environmental performance of current and future passenger vehicles: Life Cycle Assessment based on a novel scenario analysis framework. *Applied Energy*, *157*, 871-883. https://doi.org/10.1016/j.apenergy.2015.01.019

Chargefox – Australia's largest EV charging network. (n.d.). Retrieved 22 June 2023, from https://www.chargefox.com/

Denholm, P., & Short, W. (2006). An Evaluation of Utility System Impacts and Benefits of Optimally Dispatched Plug-In Hybrid Electric

Vehicles. *NREL Report NoTP-620*, *October*, 41. http://www.nrel.gov/docs/fy07osti/40293.pdf

Electric Cars, Solar & Clean Energy | Tesla. (n.d.). Retrieved 22 June 2023, from https://www.tesla.com/

Ellahi, A., Jillani, H., & Zahid, H. (2021). Customer awareness on Green banking practices. *Journal of Sustainable Finance and Investment*. https://doi.org/10.1080/20430795.2021.1977576

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology*, *17*(1), 53-64. https://doi.org/10.1111/j.1530-9290.2012.00532.x

Home - C+Charge. (n.d.). Retrieved 22 June 2023, from https://c-charge.io/

Nasukawa, T., & Yi, J. (2003). Sentiment analysis: Capturing favorability using natural language processing. *Proceedings of the 2nd International Conference on Knowledge Capture, K-CAP 2003*, *March*, 70-77. https://doi.org/10.1145/945645.945658

Paybrise. (n.d.). Retrieved 22 June 2023, from https://paybrise.app/homepage

Saura, J. R., Palos-Sanchez, P., & Grilo, A. (2019). Detecting indicators for startup business success: Sentiment analysis using text data mining. *Sustainability (Switzerland)*, *11*(3), 1-14. https://doi.org/10.3390/su11030917

Saura, J. R., Palos-Sanchez, P., & Martin, M. A. R. (2018). Attitudes expressed in online comments about environmental factors in the tourism sector: An exploratory study. *International Journal of Environmental Research and Public Health*, *15*(3). https://doi.org/10.3390/ijerph15030553

Septia Irawan, A., Shahin, B., Wangeshi Njuguna, D., Nellamkuzhi, N. J., Thiện, B. Q., Mahrouseh, N., & Varga, O. (2022). Analysis of Content, Social Networks, and Sentiment of Front-of-Pack Nutrition Labeling in the European Union on Twitter. *Frontiers in Nutrition*, *9*(April). https://doi.org/10.3389/fnut.2022.846730

Shibtoken. (n.d.). Retrieved 22 June 2023, from https://www.shibatoken.com/

Suresha, H. P., & Kumar Tiwari, K. (2021). Topic Modeling and Sentiment Analysis of Electric Vehicles of Twitter Data. *Asian Journal of Research in Computer Science*, *12*(2), 13-29. https://doi.org/10.9734/ajrcos/2021/v12i230278.

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3	Supervisory Development Programme [for the Executives of MSN Labs]	May 6-7, 2024	Dr Sinju Sankar
4	ESG Reporting and Sustainability	May 8-10, 2024	Prof Ch Lakshmi Kumari
5	Workshop on "Customer Acquisition and Retention"	May 17-18, 2024	Prof Padmaker Jadhav
6	Supervisory Development Programme [for the Executives of MSN Labs]	June 10-11, 2024	Dr Sinju Sankar
7	Happiness and Wellbeing for Managers	June 10-12, 2024	Prof Ujjal Mukherjee & Dr K Bhavana Raj
8	Leadership and Change Management	June 25-27, 2024	Prof A Sridhar Raj & Dr Anupama Dubey Mohanty
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