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From the Editors Desk:

Special Issue – II

Selected Papers from the ICSSR Sponsored Two-Day International Research Conference on "Digital Marginalisation and AI Bias: Redefining Business and Society (ICDMAI-BS 2026)"

It gives us immense pleasure to present **Special Issue – II** of the Quest Journal of Management and Research, comprising selected double-blind peer-reviewed papers from the ICSSR Sponsored Two-Day International Research Conference on **"Digital Marginalisation and AI Bias: Redefining Business and Society (ICDMAI-BS 2026)",** held on **27–28 February 2026** in hybrid mode.

The conference was organized with the objective of fostering scholarly dialogue on the transformative impact of Artificial Intelligence and digital technologies on contemporary business and society. As AI-driven systems increasingly influence decision-making processes, consumer behaviour, education, governance, finance, and sustainability, concerns regarding digital exclusion, algorithmic bias, ethical accountability, and equitable access have become central to academic and policy discussions. The conference provided an interdisciplinary platform for researchers, academicians, practitioners, and policymakers to explore these emerging challenges and opportunities.

The papers included in **Special Issue – II** reflect the expanding role of artificial intelligence, data analytics, sustainability, and algorithm-driven decision-making in shaping business and societal outcomes. Collectively, these contributions provide valuable insights into sustainable development, ethical AI adoption, digital inclusion, consumer behaviour, financial decision-making, and data-driven business strategies.

The issue opens with **"Quantifying Sustainability: A Non-Parametric Analysis of ESG Performance Across Indian Manufacturing Sectors,"** which evaluates environmental, social, and governance (ESG) performance across Indian manufacturing industries using non-parametric analytical techniques. The study contributes to the growing body of sustainability research by offering evidence-based insights into sectoral performance and the role of ESG practices in promoting responsible industrial development.

The second paper, **"Digital Marginalization and Algorithmic Bias: Challenges and Implications for Business and Society,"** examines how algorithmic systems may unintentionally reinforce inequalities in access, representation, and decision-making. The paper discusses the ethical and managerial implications of algorithmic bias while emphasizing the importance of transparency, fairness, and inclusive AI governance for sustainable digital transformation.

The third contribution, **"Algorithmic Acquisition versus Algorithmic Retention: An Empirical Analysis of Revenue Dynamics at Wayfair Inc. and eBay Inc., 2017–2024,"** investigates the strategic impact of algorithm-driven customer acquisition and retention practices on organizational revenue performance. Through an empirical analysis of two leading e-commerce platforms, the study offers valuable insights into data-driven marketing strategies and their influence on long-term business growth.

The fourth paper, **"Data-driven Consumer Insights and Ethical Marketing Practices: AI-Enabled Neuromarketing Strategy on Consumer Purchasing Behaviour in Organized, Unorganized and Online Retail Stores,"** explores the application of AI-enabled neuromarketing in understanding consumer behaviour across diverse retail environments. The study highlights the potential of advanced analytics to enhance marketing effectiveness while emphasizing the ethical considerations associated with collecting and utilizing consumer data.

The issue concludes with **"AI-Powered Financial Decision-Making: Implications for Investor Welfare,"** which examines the growing influence of artificial intelligence in financial advisory services and investment decision-making. The paper evaluates the opportunities and challenges associated with AI-assisted investment strategies, emphasizing their implications for investor welfare, financial literacy, transparency, and responsible financial innovation.

Collectively, the contributions featured in **Special Issue – II** advance our understanding of the dynamic relationship between artificial intelligence, sustainability, digital transformation, and responsible business practices. They demonstrate how emerging technologies can create significant opportunities for innovation while simultaneously highlighting the need for ethical governance, inclusive policies, and evidence-based decision-making. The findings presented herein offer valuable insights for researchers, educators, industry practitioners, and policymakers seeking to build sustainable, equitable, and responsible digital ecosystems.

We express our sincere gratitude to the **Indian Council of Social Science Research (ICSSR)** for its generous support in facilitating this international conference and promoting research on issues of contemporary relevance. We also extend our appreciation to all authors, reviewers, keynote speakers, session chairs, members of the organizing committee, and participants whose dedication, collaboration, and scholarly contributions made the conference a resounding success.

As we present **Special Issue – II,** we hope that the research published in this volume stimulates further scholarly inquiry, informed policymaking, and meaningful dialogue on the evolving challenges and opportunities associated with artificial intelligence, sustainability, digital transformation, and responsible innovation. We trust that the discussions initiated through these contributions will contribute significantly to advancing knowledge and fostering a more ethical, inclusive, and sustainable future.

Dr. Kavita Khadse,

Editor & ICSSR International Research Conference Convener

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Quantifying Sustainability: A Non-Parametric Analysis of ESG Performance Across Indian Manufacturing Sectors

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Abstract:

Purpose

This study evaluates and compare the Environmental, Social, and Governance performance of key sub-sectors within India's manufacturing industry. By analysing reported ESG indicators, the research identifies which sectors are more closely aligned with the Sustainable Development Goals and highlights the disparities that exist in sustainability adoption and implementation.

Design/Methodology/Approach

A quantitative and comparative research design was adopted. ESG data from 50 leading Indian manufacturing firms, representing the oil, chemical, metal, and automobile sectors, were collected from their Business Responsibility and Sustainability Reports, annual reports, and statutory disclosures for financial years 2021–22 and 2022–23. Using non-parametric statistical methods, including the Kruskal–Wallis test, Dunn's post hoc analysis, and the Wilcoxon signed-rank test, the study assesses both cross-sectoral differences and year-on-year variations in ESG performance.

Findings

Significant differences were observed across sectors in environmental metrics such as energy use, greenhouse gas emissions, and waste generation. Social indicators, including employee turnover, gender diversity, and CSR spending, also varied considerably. Governance factors such as dividend payout and ownership structure showed mixed alignment with sustainability benchmarks. The automobile and chemical sectors demonstrated stronger ESG integration, whereas the metal sector lagged in environmental performance.

Limitations

The analysis is limited to two financial years and focuses on the top ten companies within each sector, which may exclude smaller yet impactful firms. Reliance on self-reported secondary data may also introduce potential reporting biases.

Practical and Social Implications

The findings offer valuable insights for investors, regulators, and corporate decision-makers in identifying ESG-aligned sectors and improving sustainability benchmarking. The study underscores the increasing relevance of ESG accountability in India's manufacturing sector and highlights the need for transparent, inclusive, and responsible industrial practices that support long-term environmental and social well-being.

Keywords : *ESG, BRSR, Non-Parametric Analysis.*

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Introduction

Environmental degradation has become one of the most persistent global challenges accompanying industrial growth and economic expansions. The environmental consequences of business operations of an contributed to social tensions and ecological imbalances (Almedya & Darmansyah, 2019). Consequently corporations are now expected to balance profitability with the responsibility towards environmental and society supported by strong governance structure that build community trust and ensure long term resilience (Gray et al., 1995) In 2019, over 11,000 scientists from more than 150 nations endorsed a global statement declaring an urgent climate emergency, warning that the planet is approaching critical ecological limits that threaten both human and natural systems (Ripple et al., 2019; The Guardian, 2019).

The concept of Environmental, Social, and Governance (ESG) responsibility has evolved as a framework to address these global sustainability concerns. Since its incorporation into the United Nations Principles for Responsible Investment (UN PRI) in 2006, ESG has gained prominence in academic research, policy debates, and corporate practices (Lee et al., 2022; Tylec, 2022; Zyznarska-Dworczak, 2022; Yu & Xiao, 2022; Wang et al., 2023). The growing emphasis on ESG reflects a shift from short-term financial performance toward a broader understanding of corporate value creation that includes environmental protection, social equity, and transparent governance. The momentum intensified after the 2015 Paris Agreement, which catalyzed a surge in sustainability-oriented studies and corporate initiatives aimed at mitigating climate change and promoting responsible business conduct (Allen et al., 2016; Mio et al., 2020; Budzanowska-Drzewieck et al., 2023; Sullivan et al., 2017).

Globally, ESG considerations have become integral to investment decision-making, with investors increasingly relying on non-financial disclosures to assess corporate risk and sustainability performance (Bianchi et al., 2010; Coleman et al., 2010). ESG reporting captures a firm's environmental footprint, resource management, human rights practices, and ethical conduct. It provides transparency to both internal and external stakeholders and demonstrates a company's commitment to responsible growth (Wong, 2017). As global financial systems evolve, ESG-integrated investment models are replacing traditional frameworks that focused exclusively on economic returns (Cadman, 2012; Fijalkowska et al., 2018; Hang & Geyer-Klingeberg, 2019; Perdana & Tan, 2024). The increased focus on ESG disclosure thus serves as a strategic tool for risk management, stakeholder engagement, and sustainable competitiveness.

The global landscape of sustainability reporting continues to evolve, driven by rising investor demand for credible and standardized ESG information. Prominent international frameworks such as the Global Reporting Initiative (GRI), Carbon Disclosure Project (CDP), Sustainability Accounting Standards Board (SASB), and United Nations Global Compact (UNGC) have developed key performance indicators that help organizations assess and communicate their sustainability impact. These frameworks have guided firms in integrating sustainability into their operational and reporting systems, enhancing transparency and accountability (Das et al., 2023).

In India, the evolution of ESG and sustainability reporting has followed a distinct trajectory. Corporate Social Responsibility (CSR) was initially treated as a voluntary or philanthropic activity until the Companies Act, 2013, made CSR spending mandatory for qualifying firms. This legislative step positioned India as the first country to legally enforce CSR obligations, marking a paradigm shift from philanthropy to accountability in corporate governance. The subsequent introduction of the Business Responsibility and Sustainability Report (BRSR), replacing the earlier Business Responsibility Report (BRR), further institutionalized ESG disclosure practices.

Under guidelines issued by the Securities and Exchange Board of India (SEBI), the top 1,000 listed firms by market capitalization are now required to publish BRSR reports from FY 2022–23 onward. This transition has standardized sustainability reporting in India, enabling investors to better assess firms' non-financial performance (EY, 2021; Cyrill, 2023).

The manufacturing sector occupies a pivotal role in India's economic development, consistently contributing around 17% of GDP and employing millions. As the government seeks to expand industrial output and employment through initiatives like Make in India, the sustainability of manufacturing processes has gained policy significance (Mehta & Rajan, 2017; IBEF, 2023d). However, the sector is also a major source of energy consumption, waste generation, and carbon emissions, making it central to the national sustainability agenda. While manufacturers are increasingly disclosing their ESG performance, empirical research comparing the actual quantitative ESG data across manufacturing sub-sectors remains limited (Buallay et al., 2019).

Sustainable manufacturing therefore demands an integrated approach covering eco-efficient design, cleaner production technologies, resource optimization, waste minimization, and ethical governance. Regulatory frameworks, stakeholder expectations, and market pressures are accelerating this transition (Mallya, 2023). Against this background, the present study investigates the ESG performance of key manufacturing sub-sectors oil, chemical, cement, metal, and automobile using actual reported data. The objective is to evaluate how these sectors differ in their progress toward sustainability, thereby contributing to the understanding of India's industrial alignment with global ESG standards.

Literature Review

Sustainability reporting has become one of the critical mechanisms through which organizations communicate their environmental, social, and governance (ESG) performance. Recent research underscores that transparent disclosure of ESG data can serve as a catalyst for internal reflection and performance enhancement, helping firms align strategic decisions with long-term sustainability objectives. According to EY (2023), effective ESG reporting encourages organizations to treat sustainability data with the same rigor as financial disclosures, enabling more accurate decision-making and accountability. However, global evidence indicates that only about a quarter of firms possess robust systems to support reliable ESG reporting and assurance, reflecting significant room for improvement (KPMG, 2023).

This study focuses on five prominent sub-sectors of Indian manufacturing oil, chemical, cement, metal, and automobile each of which plays a vital role in industrial output and environmental impact. The oil and gas sector forms the backbone of India's energy infrastructure and has deep linkages with national economic growth. As India's GDP is projected to reach USD 8.6 trillion by 2040, energy demand is expected to almost double, making sustainable practices in this sector increasingly urgent (IBEF, 2023e). The sector faces mounting criticism for its heavy dependence on fossil fuels, limited transparency in emission reporting, and delayed adoption of cleaner technologies (Coffin, 2021). Recent scholarship highlights that oil and energy companies must address regulatory expectations and societal pressures by integrating low-carbon strategies while maintaining profitability (Pätäri et al., 2014; Ramírez-Orellana et al., 2023).

The chemical industry is another major contributor to India's GDP, accounting for approximately 7% and employing over two million people. Producing more than 80,000 products, it has strong linkages with agriculture, textiles, and food processing (IBEF, 2023c; Kapoor & Negi, 2022). Nonetheless, sustainability challenges persist especially concerning waste management, pollution, and the growing crisis of microplastics (Sánchez-Bayo, 2011).

Scholars argue that future competitiveness in the chemical industry will depend not only on profitability and product innovation but also on adopting cleaner technologies, promoting recyclability, and embracing circular economy models (Jain et al., 2023; Papafloratos et al., 2023). These strategies help balance economic growth with environmental stewardship and social accountability.

The cement sector occupies a unique position in India's industrial landscape, ranking second globally in production capacity and contributing over 8% of the world's installed capacity. Forecasts suggest the sector could expand at a compound annual growth rate of 4.7% between 2024 and 2032 (IBEF, 2023b). Studies highlight that the Indian cement industry is among the most efficient worldwide in energy utilization, technological adaptability, and climate-conscious production practices (Kukreja et al., 2020). Yet, as cement manufacturing remains one of the largest sources of carbon emissions, companies are increasingly expected to disclose their sustainability performance and adopt innovations that reduce CO_2 emissions in line with the Paris Agreement targets (Orozco et al., 2019).

The metal industry, particularly steel, has also experienced rapid expansion in the past decade. Domestic steel production has increased by 75% since 2008, and annual output is projected to exceed 300 million tonnes by 2030–2031 (IBEF, 2023f). India's access to high-quality iron ore and non-coking coal provides the sector with a strong resource advantage (Ministry of Steel, 2017). However, the energy-intensive and high-emission nature of metal production has placed the sector under pressure to transition toward greener operations. Research has shown that mining and metal firms are incorporating ESG frameworks to improve stakeholder relations, reduce ecological damage, and align with global sustainability standards (Michaels et al., 2022; Haagensen et al., 2023; IEA, 2023).

The automobile industry represents another critical segment of India's manufacturing base, contributing about 7% to GDP and serving as a key driver of employment and exports (IBEF, 2023a). Supported by favorable government policies and growing consumer demand, the sector has established itself as a global manufacturing hub (Miglani, 2019). Recent academic work suggests that automakers are increasingly embedding ESG principles in their strategic frameworks to enhance competitiveness and build trust with investors and customers (Billio et al., 2021; Tarmuji et al., 2016). Corporate Social Responsibility (CSR) reporting in this sector reflects a commitment to social inclusion, environmental responsibility, and greater transparency in governance (Russo Spena et al., 2018). As sustainability expectations rise, automobile firms are focusing on clean technology, circular supply chains, and workforce inclusivity to improve ESG outcomes (Dincă et al., 2023).

The increasing importance of Environmental, Social, and Governance (ESG) practices has transformed corporate sustainability from a voluntary initiative into a strategic imperative for long-term value creation. Recent empirical evidence suggests that organizations with stronger ESG disclosures exhibit improved financial performance, enhanced stakeholder confidence, and better access to capital markets. In the Indian context, the implementation of the Business Responsibility and Sustainability Reporting (BRSR) framework has significantly strengthened corporate sustainability reporting and transparency.

Bania and Biswas (2024) examined key ESG metrics across major Indian manufacturing segments and demonstrated considerable sectoral differences in environmental efficiency, social responsibility, and governance quality. Their findings indicate that sustainability performance varies substantially depending on industry characteristics and operational intensity, emphasizing the need for sector-specific evaluation models.

Similarly, Malik and Kashiramka (2024) investigated the relationship between ESG disclosure quality, firm performance, and cost of debt among Indian companies. Their study found that comprehensive ESG reporting enhances financial performance while reducing financing costs, reinforcing the strategic importance of sustainability disclosures for corporate competitiveness.

Expanding the industry-specific perspective, Paridhi and Ritika (2025) reported a significant positive association between ESG disclosures and return on assets across Indian firms, with the strength of the relationship varying across different industries. Their findings highlight the importance of sectoral analysis in understanding ESG effectiveness and support the argument that sustainability practices create measurable business value.

Within the petroleum industry, Pugazh and C. (2025) demonstrated that ESG integration contributes positively to operational performance, stakeholder trust, and long-term financial stability. Their research further emphasizes the growing importance of sustainability initiatives in traditionally carbon-intensive sectors undergoing energy transition.

From an innovation perspective, Goud (2025) established that ESG disclosure quality positively influences research and development investment and overall firm performance among Indian corporations. The study suggests that transparent sustainability practices encourage innovation and strengthen organizational competitiveness in dynamic business environments.

Recent evidence from the Indian manufacturing sector also highlights the critical role of governance mechanisms in improving sustainability performance. A study published in the International Journal of Research and Innovation in Social Science (IJRISS, 2025) reported that stronger corporate governance practices significantly enhance ESG performance and organizational accountability, supporting the integration of governance structures into sustainability strategies.

Furthermore, Arunkumar, Divya, and Chandan (2025) employed Data Envelopment Analysis (DEA) to evaluate ESG efficiency in the Indian information technology sector and identified considerable differences in sustainability efficiency among firms. Their findings demonstrate the usefulness of quantitative analytical approaches for benchmarking ESG performance and encourage the application of advanced statistical methods across industries.

Although recent studies have significantly advanced ESG research in India, existing literature primarily focuses on individual industries, financial outcomes, or disclosure quality. Comprehensive comparative analyses across multiple manufacturing sectors using robust non-parametric statistical techniques remain limited. Moreover, empirical investigations utilizing post-BRSR disclosures to evaluate year-on-year sustainability performance are still emerging. Therefore, the present study addresses these gaps by conducting a comparative non-parametric analysis of ESG performance across major Indian manufacturing sectors, providing evidence-based insights for policymakers, investors, and corporate managers.

Overall, the reviewed literature indicates that while Indian manufacturing industries are moving toward more sustainable models, progress remains uneven across sub-sectors. The empirical gap lies in comparative, data-driven analyses that evaluate ESG metrics based on actual reported values rather than narrative disclosures. The present study addresses this gap by applying non-parametric statistical tools specifically the Kruskal–Wallis test, Dunn's post hoc test, and the Wilcoxon signed-rank test to examine inter-sectoral variations in ESG performance. By quantifying differences in environmental, social, and governance dimensions, the study provides an evidence-based understanding of how Indian manufacturing sectors are progressing toward sustainability.

Research Methodology

This study adopts a quantitative, cross-sectional, and comparative research design to analyze ESG (Environmental, Social, and Governance) performance across key Indian manufacturing sub-sectors. The methodology is structured around secondary data obtained from reliable public disclosures, ensuring objectivity and replicability of results.

1. Data Source and Sample Selection

The research is based on ESG-related indicators extracted from corporate sustainability disclosures, including the Business Responsibility and Sustainability Report (BRSR), sustainability reports, and annual reports of selected firms. The BRSR, introduced by the Securities and Exchange Board of India (SEBI) in 2021, replaced the earlier Business Responsibility Report (BRR) framework to strengthen ESG transparency and accountability. This framework emphasizes nine guiding principles covering ethical business conduct, product responsibility, employee well-being, stakeholder inclusivity, environmental protection, policy advocacy, equitable development, and consumer responsibility. Since FY 2022–23, SEBI has mandated the top 1,000 listed companies by market capitalization to file BRSR reports annually, which include quantitative ESG data. In alignment with this framework, the present study selects 50 leading companies across five core manufacturing sub-sectors (a) oil (including gas and consumable fuels), (b) chemical, (c) cement, (d) metal, and (e) automobile (including auto components). From each sub-sector, the top ten firms by market capitalization were identified and included in the analysis. The dataset covers two financial years, 2021–22 and 2022–23, since the BRSR reports provide comparable ESG metrics across these years.

2. Data Analysis Framework

The study focuses on quantifiable ESG parameters reported by the selected firms. Environmental indicators include metrics such as total energy consumption, renewable energy use, greenhouse gas (GHG) emissions (scope 1 and scope 2), waste generation, recycled waste, and water consumption. Social indicators encompass employee turnover, retention, gender representation, health and safety training, CSR spending, and input material sourcing from MSMEs. Governance parameters cover shareholder patterns, dividend rates, promoter holdings, institutional shareholding, and investor complaints.

The data were first summarized using descriptive statistics (mean values and frequency distributions) to establish an overall sectoral profile. The number of companies performing above or below the mean for each ESG parameter was computed to gauge sectoral variability.

3. Statistical Techniques Employed

To test the statistical significance of inter-sectoral differences, the study employs non-parametric statistical methods, which are suitable for data that do not follow normal distribution patterns.

1. Kruskal–Wallis Test – Applied to determine whether there are statistically significant differences in ESG parameter distributions across the five manufacturing sub-sectors.
2. Dunn's Post Hoc Test – Conducted following significant Kruskal–Wallis results to identify specific sector pairs that differ in ESG performance.
3. Wilcoxon Signed-Rank Test – Used to compare ESG parameter values between the two financial years (2021–22 and 2022–23) to detect temporal shifts in sustainability performance.

These statistical tests provide robust insights into whether ESG variations are random or sector-specific, and whether measurable progress has been achieved year-on-year.

4. Ethical Considerations and Data Integrity

As the study exclusively relies on publicly available corporate disclosures, no primary data collection or human participation was involved. All information has been sourced from verifiable documents to ensure transparency, credibility, and adherence to ethical research standards.

By employing a non-parametric statistical framework on quantitative ESG data from top-performing Indian manufacturers, this study systematically identifies patterns, gaps, and progress in sustainability performance across sub-sectors. The methodological design enables a comparative and temporal analysis of ESG practices, providing empirical grounding for future research, investment evaluation, and policy formulation in the domain of sustainable manufacturing.

Results and Discussion

Table 1 presents the summary of measurement units, mean values, and the number of companies performing above and below the mean for key Environmental, Social, and Governance (ESG) parameters across 50 Indian manufacturing firms. The analysis provides a snapshot of sectoral sustainability performance and reveals significant variation in corporate practices under each ESG pillar.

Table 1. Measurement Units, Mean Values, and Distribution of Firms Above or Below Mean ESG Parameters (N = 50)

Category / Parameter	Unit of Measurement	Mean Value	No. of Firms Above Mean	No. of Firms Below Mean
A. Environmental Indicators				
Total energy consumption	Gigajoules	102,527,499.23	13	37
Energy consumed from renewable sources	Percentage	7.36	12	38
Total Scope 1 emissions	Metric tonnes of CO_2 equivalent	9,664,975.10	13	37
Total Scope 2 emissions	Metric tonnes of CO_2 equivalent	829,977.40	10	40
Total waste generated	Metric tonnes	2,263,819.28	8	42
Total recycled waste	Metric tonnes	1,893,525.49	6	44
Total volume of water withdrawn	Kilolitres	24,863,674.43	11	39
Total volume of water consumed	Kilolitres	23,643,551.21	10	40
B. Social Indicators				
Employee turnover rate	Percentage	14.26	21	29
Return-to-work rate post parental leave	Percentage	98.59	42	8
Employee retention rate	Percentage	95.84	33	17
Total number of employees	Number	8,393.08	13	37
Female employees as proportion of total workforce	Percentage	7.14	20	30

Employees with performance and career development review	Percentage of total employees	94.72	39	11
Employees trained in health and safety measures	Percentage of total employees	67.45	28	22
Employees trained in skill upgradation	Percentage of total employees	67.23	29	21
Employees trained in human rights policy	Percentage of total employees	65.98	31	19
Lost time injury frequency rate (LTIFR)	Lost time injuries per million-person hours worked	0.20	14	36
Employee fatalities	Number	0.52	9	41
Input material sourced from MSMEs/small producers	Percentage	19.13	16	34
CSR expenditure	Percentage of total CSR obligation	117.54	12	38
C. Governance Indicators				
Shareholder/investor complaints received	Number	221.07	7	43
Highest traded share price	₹ (INR)	2,452.91	13	37
Final dividend per share	₹ (INR)	16.36	7	43
Outstanding equity shares	Number	2,819,379,939.74	11	39
Total number of shareholders	Number	657,756.84	16	34
Promoter shareholding	Percentage	54.93	28	22
Foreign institutional/portfolio investor (FII/FPI) shareholding	Percentage	14.34	23	27
Mutual fund shareholding	Percentage	9.75	22	28
Insurance company shareholding	Percentage	5.53	24	26
Equity held in dematerialized form (NSDL/CDSL)	Percentage of total equity share capital	99.17	39	11

Environmental Indicators

The environmental data highlight substantial heterogeneity in energy consumption, emissions, waste generation, and water usage. The mean total energy consumption across all firms is 102,527,499.23 gigajoules, with only 26% (13 firms) reporting consumption levels above the average, reflecting the dominance of energy-intensive operations in heavy manufacturing sectors such as metal and cement. Similarly, the proportion of energy derived from renewable sources remains minimal only 12 firms (24%) exceeded the mean share of 7.36%, indicating limited adoption of renewable energy technologies within Indian manufacturing.

The findings for greenhouse gas (GHG) emissions reinforce this pattern. The mean Scope 1 and Scope 2 emissions stand at 9.66 million and 0.83 million metric tonnes of CO_2 equivalent, respectively, with most firms reporting below-average figures. This suggests that while some companies have adopted emission mitigation measures, a large proportion continue to rely heavily on conventional, carbon-intensive production systems.

In terms of waste management, only 16% of firms generated waste volumes above the mean value of 2.26 million metric tonnes, while an even smaller group (12%) recycled or reused waste above the average level of 1.89 million metric tonnes. This points to the need for more comprehensive recycling and circular economy initiatives. Similarly, both water withdrawal (mean: 24.86 million kilolitres) and water consumption (mean: 23.64 million kilolitres) show a skewed distribution, with the majority of firms reporting values below the mean, implying a concentration of high water usage among a few large, resource-intensive companies.

Social Indicators

The social parameters demonstrate stronger and more consistent performance across the sample, though disparities remain. The average employee turnover rate is relatively low at 14.26%, with nearly half of the companies (42%) showing better retention than the mean. The return-to-work rate after parental leave (mean: 98.59%) and the overall retention rate (mean: 95.84%) are both notably high, suggesting general compliance with labor welfare norms and employee continuity policies.

However, gender diversity remains a significant weakness. The share of female employees averages only 7.14%, with 60% of companies falling below the mean. This underscores the persistence of male-dominated workforces in manufacturing industries.

On a positive note, the majority of firms demonstrate strong commitment to employee development and workplace safety. Over 78% of firms exceed the mean for performance appraisal coverage (94.72%), and a majority also report strong participation in health and safety training (67.45%) and skill enhancement programs (67.23%). Similarly, human rights and policy training is expanding, with 62% of companies performing above the mean of 65.98%. The low Lost Time Injury Frequency Rate (LTIFR) of 0.20 per million-person hours and the minimal average of 0.52 fatalities per company further affirm improved occupational safety.

Engagement with smaller producers remains moderate, with 19.13% of input materials on average sourced from MSMEs. The CSR spending average of 117.54% of the mandated obligation indicates that while many firms meet minimum CSR requirements, only a minority exceed them, reflecting limited voluntary commitment beyond compliance.

Governance Indicators

Governance results reveal mixed outcomes. On average, companies received 221 shareholder complaints, with only 14% reporting above-mean figures, suggesting adequate investor grievance mechanisms. Market performance indicators show variation: the average highest traded price of ₹2,452.91 and the average dividend rate of ₹16.36 per share indicate moderate investor returns, though only a small proportion of firms (14%) exceed these means.

Ownership patterns highlight relatively high promoter concentration, averaging 54.93%, with over half of the companies (56%) above the mean. Institutional participation remains limited: the mean foreign institutional/portfolio investment (FII/FPI) is 14.34%, while mutual fund holdings and insurance company holdings average 9.75% and 5.53%, respectively. These figures indicate that while promoter-led governance continues to dominate, institutional oversight is gradually expanding. Encouragingly, nearly all companies (99.17%) maintain their equity in dematerialized form, reflecting full regulatory compliance and transparency.

Table 2 compares the proportion of firms performing above and below the mean for key environmental parameters across five major Indian manufacturing sub-sectors oil, chemical, metal, cement, and automobile. The analysis provides insights into how each sector differs in energy consumption, renewable energy usage, emission levels, waste management, and water utilization, offering an evidence-based understanding of sectoral sustainability maturity.

Table 2. Sector-Wise Distribution of Firms Above and Below the Mean for Key Environmental Parameters (in %)

Environmental Parameter	Oil Sector		Chemical Sector		Metal Sector		Cement Sector		Automobile Sector	
	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean
Total energy consumption	40	60	0	100	60	40	30	70	0	100
Energy consumed from renewable sources	0	100	10	90	20	80	10	90	80	20
Total Scope 1 emissions	30	70	0	100	50	50	50	50	0	100
Total Scope 2 emissions	20	80	10	90	60	40	10	90	0	100
Total waste generated	0	100	0	100	80	20	0	100	0	100
Total recycled waste	0	100	0	100	60	40	0	100	0	100
Total water withdrawal	30	70	10	90	70	30	0	100	0	100
Total water consumption	20	80	10	90	70	30	0	100	0	100

Energy Consumption and Renewable Energy Use

Energy consumption patterns vary widely across sectors. A relatively balanced distribution is observed in the metal sector, where 60% of firms operate above the mean total energy consumption, reflecting the industry's inherently high energy intensity. Conversely, the chemical and automobile sectors report no firms above the mean, suggesting comparatively lower energy requirements or more efficient production processes. The oil and cement sectors show moderate levels of consumption, with 40% and 30% of firms, respectively, exceeding the mean.

In terms of renewable energy utilization, the automobile sector demonstrates the strongest commitment to sustainable energy, with 80% of firms performing above the mean. This reflects growing adoption of solar and clean energy systems in response to global supply-chain sustainability pressures. In contrast, the oil and cement sectors exhibit complete reliance on non-renewable sources, with 100% of firms below the mean. The chemical and metal sectors show limited renewable integration, with only 10% and

20% of firms, respectively, exceeding average levels. These results clearly indicate that renewable energy transition remains uneven across Indian manufacturing, with heavy industries lagging far behind consumer-oriented sectors.

Greenhouse Gas Emissions

Emissions performance, measured through Scope 1 (direct) and Scope 2 (indirect) indicators, reveals stark inter-sectoral disparities. The metal and cement sectors each record balanced distributions for Scope 1 emissions, suggesting mixed performance between firms with modern emission control technologies and those with conventional production methods. The oil sector performs slightly better, with 30% of firms below mean emissions, though the overall carbon footprint remains substantial. In contrast, the chemical and automobile sectors have no firms above the mean, indicating comparatively lower emission volumes.

For Scope 2 emissions, the pattern remains similar: the metal sector shows the best performance, with 60% of companies above the mean, followed by moderate results from oil (20%) and chemical (10%) sectors. The cement and automobile industries display limited progress, with nearly all firms below the mean. These findings confirm that energy-intensive sectors, particularly metals, have started investing in emission management, while others rely on external energy suppliers with limited renewable integration.

Waste Generation and Recycling

The data reveal significant differences in waste management practices. The metal sector again outperforms others, with 80% of companies reporting above-mean waste generation and 60% demonstrating higher-than-average recycling rates. This dual pattern reflects both the material-intensive nature of the industry and its growing adoption of waste recovery systems. In contrast, all firms in the oil, chemical, cement, and automobile sectors report below-mean values for both waste generation and recycling, suggesting less focus on circular economy initiatives or reporting limitations.

Water Withdrawal and Consumption

The analysis of water-related indicators demonstrates that the metal sector is the most water-intensive, with 70% of firms above the mean in both water withdrawal and consumption. This is consistent with the sector's operational dependence on cooling, washing, and processing activities. The oil sector also records moderate water usage, with 30% of firms above the mean in withdrawal and 20% in consumption. Conversely, the chemical, cement, and automobile industries show minimal water utilization, with only 10% or fewer firms performing above the mean. These patterns suggest that while some progress has been made in adopting recycling and reuse practices, overall water efficiency remains a challenge for most manufacturing sectors.

Table 3 presents the percentage of firms performing above or below the mean for key social performance indicators across five manufacturing sub-sectors: oil, chemical, metal, cement, and automobile. The indicators encompass workforce stability, diversity, employee training, occupational safety, and corporate social responsibility (CSR) engagement. The findings highlight both progressive practices and persistent disparities in social performance within India's manufacturing ecosystem.

Table 3. Sectoral Distribution of Companies Above and Below the Mean for Key Social Parameters (in %)

Table 3. Sectoral Distribution of Companies Above and Below the Mean for Key Social Parameters (in %)										
Social Parameter	**Oil Sector**		**Chemical Sector**		**Metal Sector**		**Cement Sector**		**Automobile Sector**	
	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean
Employee turn-over rate	20	80	80	20	10	90	50	50	50	50
Return-to-work rate after parental leave	70	30	90	10	100	0	80	20	80	20
Employee retention rate	80	20	50	50	60	40	80	20	60	40
Total number of employees	40	60	0	100	40	60	10	90	40	60
Female employees as proportion of workforce	50	50	40	60	60	40	0	100	50	50
Employees receiving performance & career development review	80	20	50	50	80	20	90	10	90	10
Employees trained in health & safety measures	30	70	90	10	60	40	40	60	60	40
Employees trained for skill upgradation	50	50	70	30	50	50	60	40	60	40
Employees trained on human-rights policy & issues	40	60	80	20	70	30	40	60	80	20
Lost Time Injury Frequency Rate (LTIFR)	30	70	30	70	50	50	20	80	10	90
Number of employee fatalities	30	70	10	90	50	50	0	100	0	100

Input material sourced from MSMEs/small producers	50	50	30	70	60	40	10	90	10	90
CSR expenditure	20	80	10	90	60	40	50	50	0	100

Workforce Stability and Employee Retention

The turnover rate of employees reveals notable variation across sectors. The chemical industry leads with 80% of firms above the mean, followed by the cement and automobile sectors, where half the firms exceed the average. Conversely, the metal and oil sectors record the weakest retention, with only 10% and 20%, respectively, above the mean. This pattern reflects stronger workforce management and engagement practices in the chemical sector, where stable employment relationships are prioritized, compared to the volatility observed in resource-intensive industries.

Employee retention patterns reinforce these observations. The cement sector performs best, with 80% of firms above the mean retention rate, suggesting effective retention policies and worker satisfaction. The automobile and metal industries also show moderately strong performance (60% above mean). In contrast, the chemical and oil sectors show relatively balanced distributions, indicating varying success in retaining skilled employees.

Parental Leave and Gender Diversity

The return-to-work rate after parental leave is exceptionally high across sectors, with 90–100% of firms in the chemical, metal, cement, and automobile sectors performing above the mean. This suggests a strong adherence to gender-sensitive workplace policies and inclusive human resource practices. The oil sector trails slightly, though 70% of its firms still exceed the mean.

However, gender diversity remains limited across all industries. The proportion of female employees shows balanced representation in most sectors 50% of firms above and below the mean except for the cement industry, where all firms (100%) fall below the average. This highlights a continuing challenge for traditionally male-dominated sectors such as cement and metals to integrate gender diversity into their workforce structures.

Employee Development and Training

Indicators related to training and professional development suggest that most sectors have institutionalized employee growth programs. For instance, 80–90% of firms in the metal, cement, and automobile sectors perform above the mean in conducting performance and career development reviews. The chemical and oil sectors also show positive engagement, though with slightly more variation.

In terms of health and safety training, the chemical sector stands out, with 90% of firms above the mean consistent with its regulatory requirements for hazardous material handling. The metal and automobile sectors follow closely, with 60% of firms above average. The oil and cement sectors report weaker results, with a majority of firms below the mean, indicating the need for improved safety culture in these high-risk industries.

For skill upgradation, approximately half or more of firms in all sectors exceed the mean, demonstrating consistent efforts toward workforce enhancement. Similarly, human rights and policy training shows widespread adoption, led by the automobile (80% above mean) and chemical (80%) sectors both industries that are closely monitored for ethical compliance due to global value chain participation.

Occupational Safety and CSR Engagement

The Lost Time Injury Frequency Rate (LTIFR) results show relatively balanced patterns across sectors, though the cement industry performs best, with 80% of firms below the mean, indicating fewer workplace injuries. Fatalities are nearly non-existent in the cement and automobile sectors (100% below mean), while higher incidents are reported in oil and metal industries, where only 30–50% of firms remain above the mean safety threshold. This reinforces the need for continuous safety audits and modern risk management systems in these heavy industries.

Regarding CSR performance, sectoral differences are evident. The oil and chemical sectors record the weakest performance, with only 20% and 10% of firms, respectively, exceeding the mean. In contrast, metal (60%) and cement (50%) firms display stronger CSR participation, aligning with broader corporate responsibility frameworks. The automobile sector, however, shows the poorest engagement, with no firms above the mean, suggesting CSR activities are yet to be fully integrated into its strategic agenda despite its high consumer visibility.

MSME Sourcing and Inclusive Supply Chains

The indicator for input sourcing from micro, small, and medium enterprises (MSMEs) highlights mixed inclusion practices. The metal sector performs best, with 60% of firms sourcing above the mean proportion of materials from small producers, reflecting more localized supply networks. Conversely, the chemical and automobile sectors show limited engagement, with only 30–40% of firms above the mean, pointing to potential opportunities for expanding supplier diversity.

Table 4 presents the sectoral distribution of companies performing above or below the mean for major governance parameters, including shareholder activity, ownership composition, dividend distribution, and capital structure transparency. The results highlight contrasting levels of governance maturity across India's key manufacturing sectors.

Table 4. Sectoral Distribution of Companies Above and Below the Mean for Key Governance Parameters (in %)

Sectoral Distribution of Companies Above and Below the Mean for Key Governance Parameters (in %)										
Governance Parameter	**Oil Sector**		**Chemical Sector**		**Metal Sector**		**Cement Sector**		**Automobile Sector**	
	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean	Above Mean	Below Mean
Shareholder complaints received	30	70	10	90	10	90	10	90	10	90
High traded price	0	100	40	60	0	100	30	70	60	40
Rate of final dividend per share	0	100	10	90	0	100	10	90	50	50
Outstanding equity shares	50	50	0	100	40	60	0	100	20	80
Total shareholders	50	50	10	90	60	40	10	90	30	70
Shareholding of promoters	50	50	50	50	70	30	30	70	40	60
Shareholding of FII/FPI	50	50	40	60	50	50	20	80	70	30

Shareholding of mutual funds	20	80	50	50	20	80	60	40	70	30
Shareholding of insurance companies	70	30	40	60	50	50	30	70	50	50
Share capital held in dematerialized form (NSDL/ CDSL)	100	0	70	30	80	20	50	50	90	10

Shareholder Engagement and Market Activity

The indicator for shareholder complaints shows limited dispersion across sectors. Only 10–30% of firms in any given industry report figures above the mean, implying that most companies maintain relatively low levels of investor grievance. This may indicate satisfactory compliance with disclosure norms but could also reflect under-reporting or limited shareholder activism, especially in traditional industries such as cement and metal, where 90% of firms are below the mean.

Market-related variables, such as high traded price and dividend rate, display greater differentiation. The automobile sector demonstrates stronger stock market performance, with 60% of firms recording above-mean traded prices and 50% distributing higher dividends. In contrast, the oil and metal sectors report no firms above the mean for these indicators, suggesting subdued investor returns. The chemical and cement sectors occupy the middle ground, with modest above-average representation.

Equity Structure and Ownership Patterns

The number of outstanding equity shares and total shareholders illustrate the structural diversity of ownership across industries. The metal sector leads with 40–60% of companies above the mean in both categories, reflecting broader equity participation and possibly higher public float. Conversely, the chemical and cement sectors exhibit limited shareholder bases, with all or most companies below the mean an indicator of concentrated ownership.

Ownership concentration remains a defining feature of Indian manufacturing. Promoter shareholding averages high across all sectors, with particularly strong concentration in the metal industry (70% above mean) and moderate levels in oil and chemical sectors (each at 50%). The cement sector shows lower promoter control, suggesting greater institutional or diversified ownership.

The participation of Foreign Institutional Investors (FIIs) and Foreign Portfolio Investors (FPIs) varies significantly. The automobile sector shows the highest international investment, with 70% of firms above the mean, signaling greater global investor confidence and stronger governance standards. The chemical and metal industries exhibit moderate institutional presence, whereas cement firms lag with only 20% above the mean.

Institutional Investment and Governance Oversight

The data for mutual fund and insurance company shareholdings reveal distinct investment trends. The automobile and cement sectors attract stronger mutual fund participation (60–70% above mean), indicating growing investor interest in industries with stable cash flows and policy visibility. The oil and metal sectors, on the other hand, remain less favored by institutional investors, with 80% of firms below the mean.

Insurance company investment is more evenly distributed. The oil sector stands out, with 70% of firms above the mean, likely due to the dominance of large, well-established firms with lower perceived risk. Other sectors such as metal and automobile maintain balanced patterns, with 50% of companies in each performance category.

Capital Transparency and Compliance

A near-universal positive trend emerges for share capital dematerialization, a key governance indicator of transparency and regulatory adherence. All sectors display strong compliance with NSDL/CDSL norms: 100% of firms in the oil sector, 90% in automobiles, and 80% in metals hold fully dematerialized equity shares. This underscores the success of India's capital market reforms in mandating electronic shareholding systems that enhance investor protection and corporate transparency.

The Kruskal–Wallis test results in Table 5 reveal significant sectoral variation across all eight environmental parameters evaluated. Since all p-values are below 0.05, each null hypothesis is rejected, confirming that the distributions of environmental performance indicators are not uniform across sectors.

Table 5. Results of the Kruskal–Wallis Test for Environmental Parameters

Table 5. Results of the Kruskal–Wallis Test for Environmental Parameters		
Null Hypothesis	**p-Value**	**Result**
The distribution of total energy consumption is the same across all sector categories.	0.000	Rejected
The distribution of energy consumed from renewable sources is the same across all sector categories.	0.000	Rejected
The distribution of total Scope 1 emissions is the same across all sector categories.	0.000	Rejected
The distribution of total Scope 2 emissions is the same across all sector categories.	0.001	Rejected
The distribution of total waste generated is the same across all sector categories.	0.000	Rejected
The distribution of total recycled waste is the same across all sector categories.	0.005	Rejected
The distribution of total volume of water withdrawn is the same across all sector categories.	0.003	Rejected
The distribution of total volume of water consumed is the same across all sector categories.	0.006	Rejected

Energy Consumption and Renewable Energy Use

The highly significant results ($p = 0.000$) for both total energy consumption and energy from renewable sources indicate that energy profiles differ considerably among sectors. Energy-intensive industries such as metal and cement consume disproportionately higher energy, while automobile and chemical sectors show more moderate usage. The sharp difference in renewable energy adoption reflects sectoral disparities in technological capacity and regulatory pressure automobile firms appear to lead in renewable integration, whereas oil and cement lag behind.

Greenhouse Gas Emissions

The test results for Scope 1 and Scope 2 emissions ($p = 0.000$ and 0.001, respectively) demonstrate statistically significant differences in carbon intensity among sectors. Direct (Scope 1) emissions are particularly high in heavy industries such as metals, cement, and oil due to process-related combustion, whereas the chemical and automobile sectors report relatively lower emissions, benefiting from cleaner production methods and tighter supply-chain monitoring. The variation in Scope 2 emissions underscores uneven dependence on grid power, which still relies heavily on fossil fuels in India.

Waste Management

The results for total waste generated ($p = 0.000$) and total recycled waste ($p = 0.005$) also show significant heterogeneity. The metal sector produces the highest waste volumes but simultaneously demonstrates higher recycling rates, driven by economic incentives and the recyclability of metal by-products. In contrast, oil and cement sectors exhibit limited recycling engagement, reflecting operational and infrastructure constraints.

Water Usage and Withdrawal

The statistically significant findings for water withdrawal ($p = 0.003$) and water consumption ($p = 0.006$) suggest that water dependency varies sharply across manufacturing categories. The metal industry displays the highest consumption, consistent with its process requirements, while chemical and automobile sectors report comparatively lower figures, possibly due to water-efficient technologies and wastewater reuse systems. The results also highlight the importance of water management as a critical sustainability challenge across all sectors.

The Kruskal–Wallis results in Table 6 indicate that only a subset of social parameters exhibit statistically significant inter-sectoral variation. Specifically, differences are evident in employee turnover, female workforce participation, employee fatalities, and CSR spending, whereas most other social indicators show similar distributions across sectors. This pattern suggests that while some social aspects vary by industry type, others reflect uniform compliance with labor and welfare standards.

Table 6. Results of the Kruskal–Wallis Test for Social Parameters

Results of the Kruskal–Wallis Test for Social Parameters		
Null Hypothesis	**p-Value**	**Result**
The distribution of the employee turnover rate is the same across all sector categories.	0.001	Rejected
The distribution of the return-to-work rate after parental leave is the same across all sector categories.	0.841	Accepted
The distribution of the employee retention rate is the same across all sector categories.	0.415	Accepted
The distribution of the total number of employees is the same across all sector categories.	0.165	Accepted
The distribution of female employees as a percentage of total workforce is the same across all sector categories.	0.001	Rejected
The distribution of employees with performance and career development reviews is the same across all sector categories.	0.319	Accepted
The distribution of employees receiving health and safety training is the same across all sector categories.	0.359	Accepted
The distribution of employees receiving skill upgradation training is the same across all sector categories.	0.650	Accepted
The distribution of employees receiving human rights and policy training is the same across all sector categories.	0.068	Accepted
The distribution of Lost Time Injury Frequency Rate (LTIFR) among employees is the same across all sector categories.	0.423	Accepted

The distribution of the number of employee fatalities is the same across all sector categories.	0.023	Rejected
The distribution of input materials sourced from MSMEs/small producers is the same across all sector categories.	0.146	Accepted
The distribution of CSR expenditure is the same across all sector categories.	0.022	Rejected

Workforce Stability and Employee Retention

The test reveals a significant difference ($p = 0.001$) in employee turnover rates among sectors, leading to the rejection of the null hypothesis. High variability in turnover suggests sector-specific employment practices: industries such as metal and oil tend to experience higher workforce fluctuation due to physically demanding or cyclical work conditions, while chemical and automobile sectors exhibit more stable employment structures supported by better human resource policies.

Conversely, the return-to-work rate after parental leave ($p = 0.841$) and retention rate ($p = 0.415$) do not differ significantly across sectors. This indicates that most manufacturing firms adhere to uniform labor welfare and maternity/paternity leave regulations, possibly reflecting compliance with statutory labor codes rather than voluntary policy differentiation.

Gender Diversity and Inclusion

A statistically significant difference ($p = 0.001$) was found in the distribution of female employment, implying that gender representation varies widely among industries. The automobile and chemical sectors show higher proportions of women in their workforce, consistent with global supply-chain diversity initiatives. In contrast, cement and metal sectors remain male-dominated due to the technical and physical nature of their operations. This finding underscores the persistent gender gap in traditional manufacturing and the need for more inclusive recruitment and workplace design strategies.

Employee Development, Training, and Safety

Parameters related to employee training and performance review show no significant differences across sectors ($p > 0.05$). This suggests that most firms, irrespective of sector, follow standardized training modules and appraisal systems mandated by corporate governance and occupational safety frameworks.

The LTIFR ($p = 0.423$) and human rights training ($p = 0.068$) also display no significant differences, indicating that occupational safety standards and ethical conduct training are broadly institutionalized across manufacturing firms. However, despite these general similarities, qualitative differences may persist in implementation quality something that standardized ESG metrics alone may not capture.

Notably, the number of employee fatalities shows a statistically significant difference ($p = 0.023$), revealing that occupational safety outcomes vary across industries. High-risk sectors like metal and oil record more incidents compared to automobile and cement, where automation and advanced safety systems reduce workplace hazards.

CSR Engagement and MSME Sourcing

The analysis shows no significant difference ($p = 0.146$) in MSME sourcing, suggesting that most firms engage similarly with smaller suppliers. However, the CSR expenditure ($p = 0.022$) result is significant, implying variability in the extent and focus of corporate social investments. Firms in the metal and cement sectors, which often face community and environmental scrutiny, spend more on CSR initiatives than firms in the automobile or chemical sectors, where community interface is limited. This suggests that CSR spending may be driven more by external stakeholder expectations and regulatory visibility than by intrinsic social responsibility.

The Kruskal–Wallis test results show that nine of ten governance indicators differ significantly across manufacturing sectors ($p < 0.05$), revealing that corporate governance structures and market performance are not homogeneous within India's industrial landscape. Only share-capital dematerialization shows no significant variation, indicating universal compliance with regulatory norms.

Table 7. Results of the Kruskal–Wallis Test for Governance Parameters

Results of the Kruskal–Wallis Test for Governance Parameters		
Null Hypothesis	**p-Value**	**Result**
The distribution of the number of shareholder complaints is the same across all sector categories.	0.007	Rejected
The distribution of the highest traded share price is the same across all sector categories.	0.000	Rejected
The distribution of the final dividend rate per share is the same across all sector categories.	0.000	Rejected
The distribution of the number of outstanding equity shares is the same across all sector categories.	0.041	Rejected
The distribution of the total number of shareholders is the same across all sector categories.	0.019	Rejected
The distribution of promoter shareholding is the same across all sector categories.	0.001	Rejected
The distribution of foreign institutional/portfolio investor (FII/FPI) shareholding is the same across all sector categories.	0.004	Rejected
The distribution of mutual-fund shareholding is the same across all sector categories.	0.012	Rejected
The distribution of insurance-company shareholding is the same across all sector categories.	0.027	Rejected
The distribution of share capital held in dematerialized form (NSDL/CDSL) is the same across all sector categories.	0.065	Accepted

Shareholder Activity and Market Indicators

Significant differences in shareholder complaints ($p = 0.007$) and traded share prices ($p = 0.000$) reflect contrasting levels of investor engagement and market valuation. Automobile firms record the highest traded prices and lowest complaint ratios, suggesting strong investor confidence. In contrast, metal and oil companies face greater shareholder grievances and weaker stock performance, pointing to governance gaps and reputational risks.

The dividend rate per share ($p = 0.000$) also varies considerably, highlighting differences in payout policies: capital-intensive sectors such as cement and metal tend to retain earnings for reinvestment, while consumer-facing sectors like automobiles distribute higher dividends to signal stability and attract investors.

Ownership Structure and Shareholding Patterns

Significant variation in equity size ($p = 0.041$) and number of shareholders ($p = 0.019$) indicates differences in corporate scale and public participation.

Large diversified companies particularly in automobiles maintain broader shareholder bases, whereas family-owned or promoter-dominated firms, common in metal and cement sectors, show concentrated ownership.

The tests for promoter holdings (p = 0.001) and institutional shareholdings (FII/FPI, mutual funds, and insurance companies) all yield significant p-values (0.004–0.027). This demonstrates that external oversight and investor diversity differ sharply across industries. The automobile and chemical sectors attract higher institutional investment, correlating with better transparency and disclosure quality. In contrast, the oil and metal sectors remain dominated by promoters, which may constrain board independence and minority-shareholder influence.

Regulatory Compliance and Transparency

The only variable without a significant difference is dematerialized share capital (p = 0.065), confirming that all sectors have achieved near-complete electronic shareholding through NSDL/CDSL. This reflects uniform adherence to securities regulations and modernization of equity management systems across the board.

Table 8 presents the results of Dunn's post hoc test, which identifies the specific manufacturing sector pairs that differ significantly in their environmental sustainability performance for the year 2022–23. The test reveals multiple significant pairwise differences across energy, emissions, waste, and water-related indicators, underscoring substantial heterogeneity in environmental practices among Indian manufacturing industries.

Table 8. Results of Dunn's Test for Environmental Parameters Across Five Manufacturing Sectors (FY 2022–2023)

Results of Dunn's Test for Environmental Parameters Across Five Manufacturing Sectors (FY 2022–2023)					
Environmental Parameter	**Sample 1 – Sample 2**	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Adj. Sig.**
Total energy consumption	Automobile – Metal	23.000	6.519	3.528	0.006
	Automobile – Cement	20.800	6.519	3.191	0.021
	Chemical – Metal	−20.000	6.519	−3.068	0.032
Energy consumed from renewable sources	Oil – Automobile	−27.250	6.506	−4.188	0.000
	Metal – Automobile	−24.050	6.506	−3.697	0.003
	Chemical – Automobile	−21.150	6.506	−3.251	0.017
Total Scope 1 emissions	Automobile – Cement	27.400	6.519	4.203	0.000
	Chemical – Cement	−21.600	6.519	−3.313	0.014
	Automobile – Metal	20.700	6.519	3.175	0.022
Total Scope 2 emissions	Automobile – Metal	20.600	6.519	3.160	0.024
	Automobile – Cement	19.800	6.519	3.037	0.036
	Chemical – Metal	−19.600	6.519	−3.007	0.040

Total waste generated	Oil – Metal	−28.300	6.519	−4.341	0.000
	Chemical – Metal	−23.300	6.519	−3.574	0.005
	Automobile – Metal	22.700	6.519	3.482	0.007
	Cement – Metal	22.200	6.519	3.405	0.010
Total recycled waste	Oil – Metal	−22.450	6.518	−3.444	0.009
	Cement – Metal	19.350	6.518	2.969	0.045
Total volume of water withdrawn	Automobile – Metal	23.100	6.519	3.543	0.006
	Cement – Metal	21.000	6.519	3.221	0.019
Total volume of water consumed	Automobile – Metal	22.100	6.519	3.390	0.011
	Cement – Metal	20.000	6.519	3.068	0.032

Energy Consumption and Renewable Energy Adoption

Significant differences in total energy consumption are observed between automobile–metal ($p = 0.006$), automobile–cement ($p = 0.021$), and chemical–metal ($p = 0.032$) pairs. The positive test statistics for the automobile sector relative to metal and cement indicate lower energy intensity, suggesting that automobile manufacturing is comparatively more energy-efficient. The chemical industry's lower test statistic against metals implies moderate efficiency gains from process optimization and cleaner technologies.

For renewable energy consumption, all comparisons involving the automobile sector namely oil–automobile ($p = 0.000$), metal–automobile ($p = 0.003$), and chemical–automobile ($p = 0.017$) show significant negative test values, revealing that the automobile sector outperforms others in renewable energy use. This reflects the sector's greater adoption of solar and wind energy, possibly driven by global environmental commitments and supply-chain sustainability requirements. The oil sector's markedly low score confirms its continued dependence on fossil fuels.

Greenhouse Gas Emissions (Scope 1 and Scope 2)

For Scope 1 emissions, significant differences exist among automobile–cement ($p = 0.000$), chemical–cement ($p = 0.014$), and automobile–metal ($p = 0.022$) comparisons. The automobile sector reports significantly lower direct emissions than the cement and metal industries, which are known for energy-intensive processes such as clinker production and smelting. Similarly, the chemical sector's negative test statistic versus cement suggests that chemical firms, on average, maintain cleaner operational systems.

Scope 2 emissions, associated with electricity consumption, also vary significantly. The automobile sector again records lower indirect emissions relative to metal and cement (p-values ranging from 0.024 to 0.036), indicating relatively better energy procurement strategies or higher reliance on renewable electricity sources. The chemical–metal difference ($p = 0.040$) further supports the view that heavy industries lag in adopting cleaner energy grids.

Waste Generation and Recycling

The results for total waste generated show significant differences across multiple sector pairs, particularly oil–metal ($p = 0.000$), chemical–metal ($p = 0.005$), automobile–metal ($p = 0.007$), and cement–metal ($p = 0.010$). In all cases, the metal industry stands out for its higher waste output, consistent with the material-intensive and byproduct-heavy nature of metallurgical processes. The negative test values for oil and chemical sectors imply lower waste generation, likely reflecting process efficiencies and stricter pollution controls.

Regarding recycled waste, the test results reveal that oil–metal (p = 0.009) and cement–metal (p = 0.045) comparisons are significant. Metal-sector recycling rates are relatively higher, partly because scrap recovery is integral to its production economics. Cement firms also show improvement, supported by increased use of alternative fuels and raw materials. The oil sector remains least engaged in recycling due to limited circularity in its production chain.

Water Withdrawal and Consumption

The tests for water withdrawal and water consumption indicate consistent sectoral differences involving automobile–metal and cement–metal comparisons, with p-values between 0.006 and 0.032. The automobile and cement sectors consume considerably less water than the metal sector, demonstrating progress in adopting water-efficient technologies and recycling wastewater. The results reinforce that heavy industries remain the most water-dependent, emphasizing the urgent need for stricter water stewardship practices.

Table 9 presents the results of Dunn's post hoc test applied to social sustainability indicators across five manufacturing sectors. The test highlights significant pairwise differences for three key parameters: employee turnover, female workforce participation, and CSR expenditure. These findings confirm that social performance dimensions vary substantially across industry types, reflecting different labor structures, workforce diversity, and community engagement priorities.

Table 9. Results of Dunn's Test for Social Parameters Across Five Manufacturing Sectors (FY 2022–2023)

Results of Dunn's Test for Social Parameters Across Five Manufacturing Sectors (FY 2022–2023)					
Social Parameter	**Sample 1 – Sample 2**	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Adj. Sig.**
Turnover rate of employees	Oil – Chemical	−24.950	6.517	−3.828	0.002
	Metal – Chemical	22.200	6.517	3.406	0.010
Female employees as proportion of total workforce	Cement – Oil	23.100	6.519	3.543	0.006
Amount spent on CSR	Cement – Automobile	−23.800	6.519	−3.651	0.004
	Cement – Metal	22.100	6.519	3.390	0.010
	Automobile – Metal	19.600	6.519	3.007	0.040

Employee Turnover Rate

The turnover rate of employees shows significant inter-sectoral contrasts between oil–chemical (p = 0.002) and metal–chemical (p = 0.010) pairs. The negative test statistic for the oil–chemical comparison indicates higher employee turnover in the oil sector, likely due to physically demanding operations and contract-based employment patterns. The positive statistic for the metal–chemical pair suggests that the chemical industry exhibits more stable employment conditions, consistent with its structured work environment and formalized HR practices. Overall, the results reveal that the chemical sector demonstrates superior workforce retention, while traditional industries such as oil and metals continue to experience higher attrition.

Gender Representation

The difference in female employee participation between cement and oil sectors (p = 0.006) is statistically significant. The positive test statistic shows that cement firms employ a greater proportion of women compared to oil companies, which remain male-dominated due to operational and field-based work characteristics. This variation illustrates that gender diversity in Indian manufacturing remains uneven and heavily influenced by sectoral labor composition. Although incremental progress is visible in some industries, the results suggest that broader institutional initiatives are still needed to integrate gender inclusivity across the entire manufacturing landscape.

CSR Expenditure

CSR spending exhibits the most pronounced sectoral variation, with significant differences observed across three pairs cement–automobile ($p = 0.004$), cement–metal ($p = 0.010$), and automobile–metal ($p = 0.040$). The negative test value for the cement–automobile comparison implies that cement companies allocate more funds toward CSR activities than automobile firms. Similarly, the positive test statistic for cement–metal and automobile–metal pairs indicates that both cement and automobile sectors invest more heavily in CSR than metal industries.

These findings reflect the sector-specific nature of social accountability: the cement industry faces direct community and environmental scrutiny due to its localized production footprint, prompting higher CSR commitments. In contrast, automobile firms' CSR investments are relatively moderate and brand-oriented, while metal industries show minimal CSR engagement, likely emphasizing internal operational priorities over external social responsibility.

Table 10 presents the results of Dunn's test for governance parameters, highlighting statistically significant differences in market valuation, dividend policy, and ownership structure among India's five major manufacturing sectors. All identified comparisons (Adj. Sig. < 0.05) demonstrate that governance practices and investor engagement vary substantially by industry type.

Table 10. Results of Dunn's Test for Governance Parameters Across Five Manufacturing Sectors (FY 2022–2023)

Results of Dunn's Test for Governance Parameters Across Five Manufacturing Sectors (FY 2022–2023)					
Governance Parameter	**Sample 1 – Sample 2**	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Adj. Sig.**
High traded price (March 2023)	Oil – Chemical	−20.000	6.519	−3.068	0.032
	Oil – Automobile	−20.100	6.519	−3.083	0.031
Rate of final dividend per share	Metal – Chemical	20.100	6.504	3.090	0.030
Total number of outstanding equity shares	Chemical – Oil	24.200	6.519	3.712	0.003
	Cement – Oil	25.300	6.519	3.881	0.002
	Chemical – Metal	−22.900	6.519	−3.513	0.007
	Cement – Metal	24.000	6.519	3.681	0.003
Total number of shareholders	Cement – Oil	20.700	6.519	3.175	0.022
	Cement – Metal	19.900	6.519	3.053	0.034

Market Performance

Significant pairwise differences appear between oil–chemical (p = 0.032) and oil–automobile (p = 0.031) for the high traded price indicator. The negative test statistics show that oil-sector firms record substantially lower share-price performance relative to chemical and automobile companies. This suggests that investors assign higher market valuations to sectors with stronger disclosure standards and growth prospects. The result underscores the effect of sustainability transparency and innovation potential on investor sentiment, particularly within capital markets increasingly attentive to ESG disclosures.

Dividend Distribution Policy

The difference between metal and chemical sectors (p = 0.030) for the final dividend per share points to contrasting payout behaviors. Metal companies distribute higher dividends, possibly to maintain shareholder confidence during commodity-price volatility, while chemical firms prefer reinvestment to fund R&D and capacity expansion. This distinction reflects divergent capital-allocation strategies driven by sectoral risk profiles and growth stages.

Equity Structure and Ownership Breadth

Highly significant results for the number of outstanding equity shares (p = 0.002–0.007) demonstrate clear variation in capital structure. The cement and chemical sectors show larger equity bases compared to oil and metal, indicating broader ownership and potentially greater liquidity in their shares. The negative test statistic for chemical–metal highlights that metal firms tend to maintain smaller share bases, consistent with concentrated promoter ownership and limited public float.

The pattern is reinforced by significant results for the total number of shareholders particularly cement–oil (p = 0.022) and cement–metal (p = 0.034) pairs. These findings reveal that the cement sector enjoys wider investor participation, aligning with its moderate risk perception and steady dividend track record. Conversely, the metal and oil industries, often subject to cyclical profitability, attract fewer shareholders.

The Wilcoxon Signed-Rank results presented in Table 11 assess whether there were statistically significant year-on-year differences in environmental indicators between FY 2021–22 and FY 2022–23. Out of eight environmental parameters tested, only two energy consumption from renewable sources and Scope 2 emissions show statistically significant changes, suggesting modest but focused progress in corporate environmental performance during the study period.

Table 11. Results of the Wilcoxon Signed-Rank Test for Environmental Parameters (FY 2021–22 vs. 2022–23)

Results of the Wilcoxon Signed-Rank Test for Environmental Parameters (FY 2021–22 vs. 2022–23)			
Null Hypothesis	**z**	**Asymp. Sig. (2-tailed)**	**Result**
The median difference in total energy consumption between FY 2021–22 and FY 2022–23 equals 0.	−0.767	0.443	Accepted
The median difference in energy consumed from renewable sources between FY 2021–22 and FY 2022–23 equals 0.	−3.633	0.000	Rejected
The median difference in total Scope 1 emissions between FY 2021–22 and FY 2022–23 equals 0.	−0.700	0.484	Accepted

The median difference in total Scope 2 emissions between FY 2021–22 and FY 2022–23 equals 0.	−2.090	0.037	Rejected
The median difference in total waste generated between FY 2021–22 and FY 2022–23 equals 0.	−1.665	0.096	Accepted
The median difference in total recycled waste between FY 2021–22 and FY 2022–23 equals 0.	−1.037	0.385	Accepted
The median difference in total water withdrawal between FY 2021–22 and FY 2022–23 equals 0.	−0.835	0.404	Accepted
The median difference in total water consumption between FY 2021–22 and FY 2022–23 equals 0.	−0.741	0.459	Accepted

Renewable Energy Consumption

The most significant improvement is observed in energy consumption from renewable sources ($z = -3.633$, $p = 0.000$), indicating a meaningful increase in the adoption of clean energy across manufacturing sectors. The rejection of the null hypothesis confirms that firms have enhanced their renewable energy mix over time, aligning with India's national energy transition goals and corporate decarbonization commitments. This positive trend reflects growing awareness of sustainability disclosures under SEBI's Business Responsibility and Sustainability Reporting (BRSR) framework and the influence of global ESG benchmarking.

Scope 2 Emissions

The second significant result concerns Scope 2 emissions ($z = -2.090$, $p = 0.037$), implying a measurable reduction in indirect emissions related to purchased electricity. The decline suggests a shift toward more energy-efficient operations and possibly greater sourcing from renewable power utilities. This finding is consistent with improved energy management systems, expanded rooftop solar installations, and participation in green power purchase agreements (PPAs) among leading Indian manufacturers.

Stable Parameters

For other parameters including total energy consumption, Scope 1 emissions, waste generation, recycled waste, and water use the test results indicate no significant differences between FY 2021–22 and FY 2022–23 ($p > 0.05$). This stability suggests that while companies are maintaining baseline environmental performance, substantive structural improvements remain limited to specific areas like renewable adoption and electricity-related emissions.

The lack of significant change in waste generation and water usage highlights persistent inefficiencies in resource circularity and water conservation practices. These results may reflect the long investment cycles typical of manufacturing industries, where process-related sustainability upgrades often materialize gradually.

The Wilcoxon Signed-Rank test results presented in Table 12 examine year-on-year differences in social sustainability performance across Indian manufacturing firms. The analysis identifies statistically significant improvements in employee turnover, total employment, female representation, and health and safety training, indicating gradual strengthening of social responsibility practices between FY 2021–22 and FY 2022–23.

Table 12. Results of the Wilcoxon Signed-Rank Test for Social Parameters (FY 2021–22 vs. 2022–23)

Results of the Wilcoxon Signed-Rank Test for Governance Parameters (FY 2021–22 vs. 2022–23)			
Null Hypothesis	**z**	**Asymp. Sig. (2-tailed)**	**Result**
The median difference in employee turnover rate between FY 2021–22 and FY 2022–23 equals 0.	−2.416	0.016	Rejected
The median difference in total number of employees between FY 2021–22 and FY 2022–23 equals 0.	−3.193	0.001	Rejected
The median difference in female employee ratio between FY 2021–22 and FY 2022–23 equals 0.	−2.852	0.004	Rejected
The median difference in employees receiving performance and career development reviews between FY 2021–22 and FY 2022–23 equals 0.	−0.188	0.851	Accepted
The median difference in employees receiving health and safety training between FY 2021–22 and FY 2022–23 equals 0.	−2.010	0.044	Rejected
The median difference in employees receiving skill upgradation training between FY 2021–22 and FY 2022–23 equals 0.	−1.116	0.265	Accepted
The median difference in employees receiving human rights and policy training between FY 2021–22 and FY 2022–23 equals 0.	−1.897	0.058	Accepted
The median difference in Lost Time Injury Frequency Rate (LTIFR) between FY 2021–22 and FY 2022–23 equals 0.	−0.107	0.915	Accepted
The median difference in total fatalities between FY 2021–22 and FY 2022–23 equals 0.	−0.159	0.873	Accepted
The median difference in input materials sourced from MSMEs/small producers between FY 2021–22 and FY 2022–23 equals 0.	−1.547	0.122	Accepted
The median difference in CSR expenditure between FY 2021–22 and FY 2022–23 equals 0.	−0.964	0.335	Accepted

Workforce Stability and Employment Growth

The test reveals significant reductions in employee turnover ($z = -2.416$, $p = 0.016$) and significant increases in the total number of employees ($z = -3.193$, $p = 0.001$), confirming that manufacturing firms have improved workforce retention and expansion over the two-year period. These changes suggest a stabilization of labor structures following post-pandemic disruptions and possibly reflect renewed hiring momentum driven by economic recovery and production growth in core industries. The decline in attrition also implies better human resource management practices and greater employee engagement initiatives.

Gender Inclusion

A significant improvement in female employee participation ($z = -2.852$, $p = 0.004$) indicates measurable progress in gender diversity across manufacturing enterprises. This positive shift reflects the gradual success of corporate inclusion policies, gender-sensitive recruitment drives, and government-led initiatives encouraging women's participation in the industrial workforce. However, while statistically significant, this increase should be interpreted as incremental rather than transformational, as women's representation in manufacturing still remains relatively low in absolute terms compared to service sectors.

Employee Training and Workplace Safety

The health and safety training parameter ($z = -2.010$, $p = 0.044$) also shows a statistically significant improvement, suggesting that firms have increased their commitment to occupational safety and compliance with labor welfare mandates. The results align with stronger regulatory oversight under India's Occupational Safety, Health, and Working Conditions Code, coupled with higher investor scrutiny of workplace safety metrics in ESG disclosures.

Other training-related indicators skill upgradation ($p = 0.265$), human rights training ($p = 0.058$), and performance review coverage ($p = 0.851$) do not exhibit significant change. This stability implies that while safety initiatives are expanding, broader employee development and rights-based training programs have not seen comparable acceleration.

CSR and MSME Engagement

The absence of significant year-on-year change in CSR expenditure ($p = 0.335$) and MSME sourcing ($p = 0.122$) suggests that firms are maintaining compliance-based CSR activities and stable supplier relationships rather than scaling up new social investments. These parameters often evolve slowly due to long-term community partnerships and fixed procurement structures, which may explain the observed consistency.

Similarly, non-significant differences in LTIFR ($p = 0.915$) and fatalities ($p = 0.873$) indicate that workplace safety performance has remained steady, with no marked improvement or deterioration over the period likely reflecting already low injury rates among large, listed firms.

Table 13 reports the Wilcoxon Signed-Rank Test outcomes for governance indicators, comparing changes between FY 2021–22 and FY 2022–23. Out of ten parameters, five show statistically significant differences, demonstrating measurable improvements in shareholder participation and institutional investment patterns across Indian manufacturing firms.

Table 13. Results of the Wilcoxon Signed-Rank Test for Governance Parameters (FY 2021–22 vs. 2022–23)

Results of the Wilcoxon Signed-Rank Test for Governance Parameters (FY 2021–22 vs. 2022–23)			
Null Hypothesis	**z**	**Asymp. Sig. (2-tailed)**	**Result**
The median difference in the number of complaints received from shareholders/investors between FY 2021–22 and FY 2022–23 equals 0.	−2.330	0.026	Rejected
The median difference in the high traded price between FY 2021–22 and FY 2022–23 equals 0.	−1.667	0.108	Accepted
The median difference in the rate of final dividend per share between FY 2021–22 and FY 2022–23 equals 0.	−0.328	0.743	Accepted
The median difference in the total number of outstanding equity shares between FY 2021–22 and FY 2022–23 equals 0.	−1.964	0.050	Accepted

The median difference in the total number of shareholders between FY 2021–22 and FY 2022–23 equals 0.	−2.727	0.006	Rejected
The median difference in promoter shareholding between FY 2021–22 and FY 2022–23 equals 0.	−0.461	0.509	Accepted
The median difference in FII/FPI shareholding between FY 2021–22 and FY 2022–23 equals 0.	−2.235	0.025	Rejected
The median difference in mutual fund shareholding between FY 2021–22 and FY 2022–23 equals 0.	−2.415	0.016	Rejected
The median difference in insurance company shareholding between FY 2021–22 and FY 2022–23 equals 0.	−3.304	0.001	Rejected
The median difference in share capital held in dematerialized form between FY 2021–22 and FY 2022–23 equals 0.	−0.330	0.741	Accepted

Shareholder Relations and Corporate Transparency

The number of complaints received from shareholders/investors significantly decreased ($z = -2.330$, $p = 0.026$), indicating improved corporate communication and grievance resolution mechanisms. This result suggests that listed manufacturing firms have strengthened investor engagement and compliance with SEBI's enhanced disclosure and redressal mandates. A decline in shareholder complaints also reflects greater confidence in digital reporting systems and corporate governance transparency.

Ownership Structure and Investor Participation

A significant increase in the total number of shareholders ($z = -2.727$, $p = 0.006$) highlights the expanding investor base of Indian manufacturing companies. This trend points to growing retail participation and institutional confidence in the manufacturing sector, driven by post-pandemic economic recovery and government-led initiatives promoting "Make in India."

Similarly, significant differences in FII/FPI shareholding ($z = -2.235$, $p = 0.025$), mutual fund holdings ($z = -2.415$, $p = 0.016$), and insurance company investments ($z = -3.304$, $p = 0.001$) demonstrate dynamic shifts in institutional investment portfolios. The data imply that financial institutions are recalibrating their equity exposure, potentially in response to corporate ESG disclosures and sector-specific sustainability ratings.

The increase in mutual fund and insurance holdings is particularly noteworthy as it reflects the growing preference of domestic institutional investors for stable, well-governed companies. Meanwhile, the rise in FII/FPI participation signifies renewed global investor confidence in India's manufacturing resilience and regulatory transparency.

Stable Parameters

The high traded price, dividend payout, and outstanding share volume show no significant change ($p > 0.05$), suggesting market valuation stability and consistent dividend policies over the two years. Similarly, the promoter shareholding remains steady ($p = 0.509$), indicating no substantial ownership restructuring or dilution. The share capital held in dematerialized form also remains unchanged ($p = 0.741$), consistent with near-complete dematerialization in compliance with SEBI norms.

Conclusion

This study examined the environmental, social, and governance (ESG) performance of leading Indian manufacturing firms using non-parametric statistical techniques, including the Kruskal–Wallis, Dunn's post hoc, and Wilcoxon Signed-Rank tests. The findings provide a comprehensive view of how sustainability practices vary across sectors and evolve over time.

The analysis confirms that ESG performance in Indian manufacturing is highly heterogeneous across industries. Significant sectoral differences were observed for most environmental and governance indicators, particularly in energy efficiency, greenhouse-gas emissions, and ownership structures. The automobile and chemical sectors consistently demonstrated stronger performance, reflecting greater adoption of renewable energy, lower emission intensity, and more diversified investor participation. In contrast, the metal, cement, and oil sectors showed relatively weak environmental outcomes, attributed to energy-intensive operations and slower technological transitions.

The social dimension revealed moderate yet targeted improvements. Between FY 2021–22 and FY 2022–23, firms achieved measurable gains in workforce retention, gender inclusion, and health and safety training, indicating growing institutional commitment to employee welfare and equitable practices. However, skill enhancement, human-rights sensitization, and CSR spending remained largely unchanged, suggesting that many social initiatives are still compliance-driven rather than strategically embedded.

Governance analysis highlighted steady progress toward greater transparency and investor inclusivity. The significant rise in the number of shareholders and institutional investments, coupled with fewer shareholder complaints, signals enhanced corporate accountability and improved market confidence. Nevertheless, the stability of promoter holdings and dividend policies implies that deeper structural reforms in board diversity, disclosure rigor, and stakeholder oversight are still evolving.

Taken together, the results portray a manufacturing sector that is transitioning from regulatory compliance to performance-driven sustainability, though unevenly across industries and ESG pillars. Progress has been most evident in energy transition and investor governance, while social and waste-management practices require stronger policy alignment and capacity building.

In practical terms, the study underscores the need for sector-specific sustainability roadmaps, integrated ESG reporting standards, and fiscal incentives for clean technology adoption. For policymakers, the evidence supports the design of differentiated strategies that balance industrial growth with responsible production. For managers and investors, the findings highlight that sustained ESG improvements are not only ethical imperatives but also essential to long-term competitiveness, capital access, and corporate legitimacy.

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Digital Marginalization and Algorithmic Bias: Challenges and Implications for Business and Society

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Abstract:

The rapid adoption of Artificial Intelligence (AI) across business and societal domains has transformed decision-making processes, service delivery, and organizational efficiency. However, AI systems may reproduce existing inequalities through biased datasets, opaque algorithms, and unequal digital access. This paper examines digital marginalization and algorithmic bias, their implications for business and society, and the need for responsible AI governance. Using a descriptive and conceptual research design based on secondary data, the study reviews existing literature, policy reports, and real-world cases. The paper concludes that ethical AI, transparency, accountability, and inclusive digital policies are essential for balancing innovation with social justice.

Keywords : *Artificial Intelligence, Digital Marginalization, Algorithmic Bias, Ethical AI, Inclusive Development, Responsible Innovation*

1. Introduction:

Artificial Intelligence has become a critical component of modern business operations and public administration. Organizations increasingly rely on AI for recruitment, credit scoring, customer service, marketing, and governance. While AI promises efficiency and objectivity, concerns have emerged regarding algorithmic bias and digital exclusion. Marginalized populations often face disadvantages due to limited digital access, poor representation in training datasets, and automated decision-making systems. This paper explores these challenges and their implications for businesses and society.

2. Research Objectives:

1. To examine the causes of algorithmic bias in AI systems.
2. To analyze the impact of digital marginalization on vulnerable communities.
3. To evaluate the business and societal implications of biased AI systems.
4. To propose strategies for responsible and inclusive AI adoption.

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3. Review of Literature:

Existing research suggests that AI systems frequently inherit historical biases from training data. Cathy O'Neil (2016) argued that opaque algorithms can reinforce inequality. OECD (2019) emphasized transparency, fairness, and accountability in AI systems. UNESCO (2021) highlighted ethical concerns related to discrimination and exclusion. Studies on the digital divide indicate that unequal access to technology continues to affect education, employment, and financial inclusion, particularly in emerging economies. Researchers have also stressed the importance of explainable AI and human oversight in reducing discriminatory outcomes.

4. Research Methodology:

This study adopts a descriptive and conceptual research design. Data were collected from secondary sources including academic journals, books, policy reports, government publications, OECD reports, UNESCO documents, World Bank studies, and industry white papers. A thematic analysis approach was used to identify recurring themes related to algorithmic bias, digital exclusion, ethical AI, and governance. Case-study analysis was also employed to illustrate real-world implications of biased AI systems.

5. Case-Based Examples and Discussion:

Case 1: Amazon's AI Recruitment Tool

Amazon reportedly discontinued an AI recruitment system after discovering that it favored male candidates because the model had been trained on historical hiring patterns.

Case 2: Apple Card Credit Limit Controversy

Public reports indicated concerns that women received lower credit limits than men despite similar financial profiles, raising questions about fairness in automated lending systems.

Case 3: Aadhaar and Digital Exclusion in India

Instances of authentication failures in welfare delivery systems demonstrated how technology-dependent processes may exclude vulnerable citizens from essential services.

These cases demonstrate that algorithmic systems can unintentionally reproduce social and economic inequalities when fairness safeguards are absent.

6. Business and Societal Implications:

Business Implications:

- Reputational damage and loss of customer trust.
- Legal and regulatory risks.
- Reduced workforce diversity.
- Poor-quality decision-making.

Societal Implications:

- Reinforcement of existing inequalities.
- Reduced access to employment and financial services.
- Exclusion from public welfare systems.
- Increased social distrust in technology.

7. Recommendations:

Organizations should implement fairness audits, diverse training datasets, explainable AI mechanisms, and regular bias assessments. Policymakers should establish stronger AI governance frameworks, transparency standards, and accountability mechanisms. Investments in digital literacy and infrastructure are necessary to bridge the digital divide and promote inclusive participation in the digital economy.

8. Conclusion:

Artificial Intelligence has immense potential to transform business and society. However, without appropriate safeguards, AI systems can amplify historical inequalities and contribute to digital marginalization. The analysis highlights that biased datasets, limited transparency, and unequal access to digital infrastructure are among the primary drivers of exclusion. Real-world cases demonstrate that algorithmic decisions can affect employment opportunities, access to credit, and public services. Therefore, organizations must adopt responsible AI practices that prioritize fairness, accountability, and transparency. Policymakers should strengthen regulatory frameworks while promoting digital inclusion initiatives. A balanced approach that combines innovation with ethical governance will help ensure that AI serves as a tool for inclusive and sustainable development rather than a source of discrimination and exclusion. Future research may explore quantitative assessments of AI bias across industries and evaluate the effectiveness of emerging regulatory interventions.

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Algorithmic Acquisition versus Algorithmic Retention: An Empirical Analysis of Revenue Dynamics at Wayfair Inc. and eBay Inc., 2017–2024

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Abstract:

This paper compares revenue dynamics at two e-commerce firms with very different go-to-market logic: Wayfair, a retail-led, inventory-light merchant, and eBay, a marketplace-led intermediary. Using 30 quarterly observations per firm (Q2 2017–Q3 2024) from SEC filings and FRED, we run descriptive statistics, an F-test for variance equality, one-way ANOVA across pre-COVID, COVID, and post-COVID regimes, and multiple regression with a full diagnostic write-up. Wayfair's revenue growth is far more volatile than eBay's ($F = 7.09$, $p < .001$), and a regression of revenue on operating expenditure, unemployment, and the federal funds rate explains much more of Wayfair's variance (adjusted $R^2 = 0.92$) than eBay's (0.50). We argue this fits a distinction worth taking seriously: an algorithmic acquisition architecture, where revenue ties mechanically to paid, propensity-modelled acquisition, versus an algorithmic retention architecture, where revenue decouples from marketing spend through organic search relevance and seller-funded visibility markets. Because the evidence is from two firms, we treat this as a comparative case study that motivates a testable typology rather than a population-level test, with real space given to that scope limit, to confounded firm-level effects, to reverse causality, and to the larger study the typology would need.

Keywords : *algorithmic marketing, algorithmic acquisition, algorithmic retention, e-commerce business models, Wayfair, eBay, marketplace-led model, retail-led model.*

1. Introduction

1.1 Background and Motivation

E-commerce gets talked about as one industry, but it isn't. At least two architectures sit under that label: a retail-led model, where the platform owns inventory and acts as principal, and a marketplace-led model, where it connects buyers and sellers without taking title to goods. These differ in balance-sheet structure, but also, we think, in how each one's marketing algorithms do their job.

That second difference is the paper's subject. Rather than treating algorithmic marketing as one capability firms have more or less of, we split it into two orientations: an acquisition orientation, using machine learning to identify, bid for, and convert new customers (propensity scoring, real-time bidding, multi-touch attribution); and a retention orientation, using algorithms to make existing listings and users more discoverable and trustworthy (semantic

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search, structured metadata, seller-funded visibility markets). Wayfair and eBay illustrate these two orientations about as clearly as two public companies are likely to, given their documented technology histories, so we ask whether their financials behave the way the framework predicts.

Two firms can't test a population-level claim about retail-led or marketplace-led platforms in general, however careful the statistics. What the data can support is a within-firm test, over time, of whether each company's revenue behaves as its documented strategy predicts, plus a comparison of how strongly that holds across both. That's the study we ran.

1.2 Research Question and Objectives

Two questions organise the paper: do Wayfair and eBay differ in revenue-growth volatility by more than sampling noise would explain (RQ1), and do they differ in how strongly revenue tracks operating expenditure and macro conditions in a way plausibly tied to their algorithmic strategies rather than confounding firm-level factors (RQ2)?

Five objectives follow: characterising each firm's risk profile; testing formally for a variance difference; testing for structural breaks across pandemic-era regimes; estimating, per firm, how revenue relates to spending and macro conditions with full diagnostics and honest treatment of endogeneity; and formalising the acquisition/retention typology with explicit conditions for testing it on a larger sample.

2. Literature Review

2.1 E-Commerce Business Models: Retail-Led versus Marketplace Platforms

E-commerce isn't one business model. Early work treated firms as digital extensions of traditional retailers (Bakos, 1998; Amit & Zott, 2001); scholars later split merchant-based (retail-led) firms from intermediary-based (marketplace-led) ones (Rochet & Tirole, 2003; Hagiu, 2014). Retail-led firms act as principals, controlling pricing and experience and carrying inventory risk, buying differentiation at the cost of heavy logistics and marketing spend (Brynjolfsson, Hu, & Rahman, 2013). Marketplace-led platforms monetise participation instead (Parker, Van Alstyne, & Choudary, 2016), scaling through network effects and tending toward lower volatility and higher margins (Cusumano, Gawer, & Yoffie, 2019). Large-sample comparisons across the two models are rare; we use the distinction as a backdrop for a sharper, algorithmic one.

2.2 Algorithmic Marketing: Acquisition versus Retention

Algorithmic marketing automates targeting, bidding, pricing, and personalisation (Katsov, 2018), splitting into demand-generation systems that convert new customers through paid channels and relevance systems that match existing supply and demand without buying attention propensity modelling and real-time bidding versus semantic search and structured-data ranking. Multi-touch attribution, apportioning conversion credit across touchpoints via cooperative game-theoretic rules like the Shapley value (Shapley, 1953), matters here: a firm whose bidding depends on that data is exposed to anything degrading it, like a platform-level tracking change. That mechanism is what we lean on later, discussing Wayfair's post-2021 shift.

We call these orientations algorithmic acquisition (bidding for a new customer) and algorithmic retention (surfacing existing inventory to a present user). Section 4 formalises this and ties it to Wayfair's and eBay's histories a comparison, as far as we know, not previously made for revenue volatility and expenditure elasticity.

2.3 Operating Leverage and Revenue Volatility

Operating leverage theory offers a reason these architectures might diverge: firms with high fixed and semi-variable costs see profitability amplified by demand swings (Mandelker & Rhee, 1984), and retail-led firms' heavy marketing and fulfilment costs should make revenue more spend-sensitive (Levinthal & Wu, 2010). Empirical work finds positive OpEx-revenue associations at merchant-based firms (Srinivasan, Anderson, & Ponnavolu, 2002; Anderson, Fornell, & Lehmann, 1994), while platform-based firms show diminishing returns to spending (Eisenmann, Parker, & Van Alstyne, 2011). That association is consistent with several causal stories, though spending driving revenue, revenue driving spending, or both moving with seasonal demand an ambiguity central to Section 6.

2.4 Platform Economics and Revenue Stability

Network effects explain marketplace stability: platform value rises with participation on each side, stabilizing volume once critical mass is reached (Katz & Shapiro, 1985), and mature platforms can show predictable revenue through fluctuating macro conditions (Evans & Schmalensee, 2016). eBay-type marketplaces have been described as utility-like infrastructure where incremental spending buys limited growth but supports trust (McIntyre & Srinivasan, 2017).

2.5 Macroeconomic Conditions and Demand

Rising unemployment should reduce discretionary spending (Keynes, 1936; Friedman, 1957), but e-commerce can respond asymmetrically as consumers substitute toward cheaper alternatives (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020). COVID-era households shifted spending toward home goods, a "nesting effect" (Sheth, 2020) whose size varied by business model (Guthrie, Fosso-Wamba, & Arnaud, 2021), tested directly in Section 6.3. We treat the pandemic as a known shock useful for structural-break testing while staying cautious about category effects: furniture and general-merchandise demand were hit differently for reasons unrelated to marketplace structure.

2.6 Interest Rates and Digital Firm Performance

Higher rates constrain expansion and raise working-capital costs for inventory-exposed firms (Bernanke & Gertler, 1995) and suppress credit-financed purchases of high-ticket goods (Mishkin, 1996). Asset-light platforms have been argued to be less rate-sensitive than inventory-dependent retailers (Farrell & Shapiro, 2019), though the short-run impact remains unsettled tested in Section 6 via the federal funds rate.

2.7 Research Gap and Contribution

Three gaps motivate the study: business-model literature rarely connects to specific algorithmic technologies; quantitative comparisons rarely report a full diagnostic battery or address endogeneity; and little work pairs a documented technology history with a firm's statistical signature. Our contribution: a transparent, fully diagnosed comparison of two well-documented firms, organised around an explicit typology, with the limits of n = 2 stated plainly.

3. Conceptual Framework & Theoretical Background

3.1 Business Model Distinction

Wayfair controls pricing, marketing, logistics, and customer service, recognising revenue on a gross basis and bearing demand risk directly. eBay facilitates transactions without holding inventory, earning revenue mainly through fees and advertising, scaling through network effects. This is the standard retail-led/marketplace-led split (Rochet & Tirole, 2003; Hagiu, 2014), and the backdrop for Section 4's typology.

3.2 Case Selection: Rationale and Limitation

We picked Wayfair and eBay for three reasons, each with a limitation.

- Representativeness: Wayfair and eBay were selected because they represent markedly different approaches to e-commerce value creation: a supplier-direct retail model and a marketplace intermediary model. This contrast makes them useful comparative cases for exploring the proposed acquisition-versus-retention framework.

However, each firm remains a single case, meaning that category effects, firm-specific characteristics, and business-model effects are inherently confounded and cannot be statistically separated within the present design.

- Data reliability. Both files standardised, audited quarterly statements with the SEC across the full window, supporting measurement validity for these two firms but not beyond them.
- Convergent scale. By Q3 2024, Wayfair's quarterly revenue (≈$2,880M) and eBay's (≈$2,500M) had converged, holding firm size roughly constant for that quarter. It doesn't hold scale constant across the full period Wayfair's range is far wider than eBay's (Section 6.1) and says nothing about other stable differences (product category, customer base, capital structure, management) that could equally explain the results (Sections 6.5, 7).

Given these limits, Section 6's results should be read as a within-firm, over-time description of how each company's revenue has moved with its own spending and macro conditions, not an estimate of a population parameter for either business-model class.

3.3 Operating Leverage and Macroeconomic Variables

Operating leverage theory holds that cost structure amplifies revenue swings: firms with high fixed and semi-variable costs, typical of retail-led models, should see revenue more spending-sensitive than firms with mostly variable, demand-linked costs. Two macro variables enter the model: unemployment, which may reduce demand while pushing substitution toward cheaper goods that could favour marketplaces, and the federal funds rate, which affects borrowing and discretionary spending, with a stronger expected effect on retail-led firms selling high-ticket, credit-financed items.

3.4 Company Background

Wayfair Inc.

Founded in 2002 by Niraj Shah and Steve Conine, Wayfair later consolidated into a single pure-play home-goods retailer running an inventory-light, supplier-direct model. COVID-era demand for furniture surged as people spent more time at home; as demand normalised, the company faced margin pressure consistent with sensitivity to housing activity, rates, and discretionary income. Wayfair now operates across North America and Europe, competing on delivery and digital experience.

eBay Inc.

Founded in 1995 by Pierre Omidyar as an online auction site, eBay evolved into a major consumer marketplace across many categories, earning revenue mainly through transaction fees, advertising, and seller tools rather than owning inventory a structure that has historically supported resilience in downturns, as buyers seek resale alternatives and sellers monetise existing assets. eBay now operates in more than 190 markets, leaning on liquidity, trust, and user experience as growth levers, a contrast to Wayfair's paid demand generation.

4. The Algorithmic Acquisition/ Algorithmic Retention Framework

This section formalises the typology from Section 2.2 and applies it to Wayfair's and eBay's technology histories, reconstructed from public reporting and industry commentary (Katsov, 2018) as an interpretive lens for Section 6's patterns, not a causally identified account of why they occur.

4.1. Formal Definition

An algorithmic acquisition architecture makes discrete, priced decisions to acquire attention for a specific potential customer, with the cost borne by the platform, effectiveness depending on cross-channel attribution fidelity. An algorithmic retention architecture decides how to rank or surface existing inventory to users already present, shifts visibility cost to sellers, and depends on internal listing data rather than external attribution. These are orientations, not exclusive labels most platforms mix both. The claim we test is comparative: Wayfair leans more acquisition-type than eBay, and that weighting tracks Section 6's differences.

4.2 Testable Propositions

1. P1 (Volatility): A heavier acquisition orientation predicts higher revenue-growth variance, holding firm scale roughly constant.
2. P2 (Expenditure elasticity): A heavier acquisition orientation predicts a larger revenue-OpEx coefficient.
3. P3 (Signal sensitivity): An acquisition-oriented platform should show a slowdown coincident with attribution-degrading events; a retention-oriented one should be comparatively insensitive.

Section 6 tests P1 and P2 directly. P3 is discussed only narratively below, since this dataset lacks the event-study design a discontinuity test need.

4.3 Wayfair as an Acquisition-Oriented Case

Industry accounts describe Wayfair shifting, starting around 2017–2018, from manual media buying to proprietary bidding systems ("Athena," "Magellan") using propensity models to bid for placement (Katsov, 2018), and the 2019–2020 CastleGate logistics expansion alongside a shift toward geo-spatial demand forecasting. Both are acquisition-type: priced, data-dependent decisions aimed at winning a transaction, with costs borne by the platform.

Apple's 2021 App Tracking Transparency update restricted cross-app tracking and, by a wide industry account, degraded the attribution data that an acquisition-oriented bidder depends on. We treat this as context for Wayfair's post-2021 data, not a tested mechanism, since our dataset has no direct attribution measure. The 2023–2024 stabilisation plausibly coincides with broader adoption of tracking-independent, AI-assisted conversion tools, but again, untested here.

4.4 eBay as a Retention-Oriented Case

eBay's history fits a heavier retention orientation: an image-search feature launched in late 2017, a 2018–2020 push for standardised listing metadata, and Promoted Listings, expanded from 2019, shifting incremental visibility cost to sellers bidding within eBay's own results retention-type, since the marginal cost sits with participants and the value driver is existing-inventory relevance, not external acquisition. This fits the weak OpEx-revenue association in Section 6.4 and eBay's lower revenue variance in Section 6.2: a platform leaning on internal relevance should be less exposed to its own marketing budget.

Dimension	Algorithmic Acquisition	Algorithmic Retention
Marginal revenue-generating action	Algorithm bids for attention/placement to convert a new or lapsed customer	The algorithm ranks or surfaces existing listings to a user already on-platform
Primary input data	Cross-channel behavioural and attribution data (clicks, impressions, conversions)	Structured item/listing metadata, on-platform search and engagement data
Cost locus	Borne directly by the platform as paid media expenditure (operating expense)	Substantially shifted to sellers via paid visibility products (e.g., promoted listings)

Expected revenue-OpEx coupling	Tight and mechanical: revenue should move with acquisition spend, other things equal	Loose: revenue depends more on engagement/ liquidity than on platform marketing outlay
Principal external vulnerability	Attribution/ signal degradation (e.g., platform-level tracking restrictions)	Search/relevance-algorithm changes by the platform itself; seller supply shocks
Predicted volatility signature	Higher revenue variance; stronger comovement with discretionary marketing spend	Lower revenue variance; weaker comovement with marketing-type spend

Table 1: Summary of the algorithmic acquisition and algorithmic retention typology

4.4 Scope of the Framework

This doesn't claim all retail-led platforms are acquisition-oriented or all marketplaces retention-oriented that correspondence is itself an empirical question, and the two could diverge. The narrower claim: Wayfair and eBay illustrate the typology's two ends unusually clearly, which is why we picked them, and the typology offers a candidate mechanism for Section 6's findings. Testing it across a broader sample, checking whether orientation rather than business-model type is the operative variable, is the natural next step (Section 8).

The framework is intended as an interpretive lens rather than a directly observed construct. Because the study does not measure algorithmic acquisition or retention intensity directly, the framework should be viewed as a theory-driven explanation of observed financial patterns rather than a verified causal mechanism.

5. Methodology

5.1 Data Collection

Quarterly revenue and operating-expense data for both firms come from SEC filings (10-K and 10-Q); unemployment and the effective federal funds rate come from FRED, converted to quarterly averages. The dataset runs 30 quarters per firm, Q2 2017 through Q3 2024 two firms over time, not a cross-section of many, so every inferential statistic below describes these two firms in this window, not a broader population (Sections 3.2, 6.5).

5.2 Analytical Techniques

Four steps, applied identically to each firm: descriptive statistics on quarterly revenue; an F-test for equality of variances on growth rates; one-way ANOVA across pre-COVID (2018–2019), COVID (2020–2021), and post-COVID (2022–2023) regimes; and multiple regression of revenue on operating expenditure, unemployment, and the federal funds rate, with a full diagnostic battery.

5.3 Diagnostic Testing Plan

For each regression, we checked a predictor correlation matrix (for variance inflation factors), scatterplots against revenue (linearity), a residuals-versus-fitted plot (homoscedasticity), predictor histograms and residual inspection (approximate normality). Where a diagnostic follows algebraically from numbers already reported VIFs, from the correlation matrix we report the computed value in Section 6.4, we report the visual check actually performed and flag the formal statistic as something to compute before finalising. We'd rather flag a gap than invent a number.

5.4 Endogeneity and Threats to Causal Interpretation

The Section 6.4 regression relates revenue to operating expenditure and two macro variables. The OpEx coefficient isn't a causal estimate, for three reasons:

reverse causality, since firms often set budgets as a function of expected or realized sales; omitted variables, since revenue and spending both plausibly respond to something outside the model, like seasonal demand; and time-invariant firm effects, since each regression runs on one firm's time series and can't separate the OpEx effect from any other slow-moving trait of that firm. With only two firms, pooling them with fixed effects wouldn't identify anything meaningful, since firm and business-model type are perfectly collinear in a two-firm sample so we report the two regressions side by side.

None of this invalidates the regression as description: it's informative about how strongly revenue and spending co-moved within each firm, which is what the research questions ask. What it rules out is reading the coefficients as causal effect sizes; we call them measures of association instead. A credible causal estimate would need an instrument for OpEx unrelated to contemporaneous demand, a natural experiment, or a longer panel supporting fixed-effects estimation, discussed further in Section 8.

6. Empirical Results

6.1 Descriptive Statistics and Risk Profiles

Despite similar average quarterly revenues, Wayfair exhibits a standard deviation more than five times that of eBay, indicating substantially higher revenue volatility. Distributional measures further reveal greater tail risk and variability in the retail-led model, while the marketplace-led model demonstrates revenue stability and predictability (Table 1 and Figure 1).

Statistic	Wayfair (Retail)	eBay (Marketplace)
Mean	$2,681.30 M	$2,600.83 M
Median	$2,860 M	$2,578 M
Mode	$3,120 M	$2,613M
Standard Deviation	$831.98 M	$162.67 M
Range	$3,178 M	$695 M
Kurtosis	-0.61	0.51
Skewness	-0.26	0.73
Count	30	30

Table 2: Comparison of descriptive Statistics

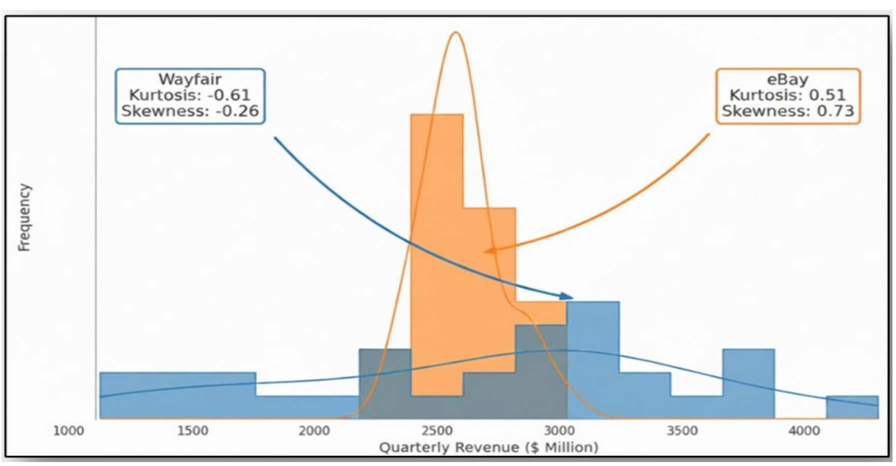


Figure 1: Comparison of descriptive Statistics

Findings:

1. **The Scale vs. Stability Paradox:** Both firms operate at a surprisingly similar scale, with mean quarterly revenues around $2,600 million. However, this similarity is superficial. The Standard Deviation for Wayfair ($831.98 M) is more than five times higher than that of eBay ($162.67 M). This is a massive divergence in risk profile. It suggests that while Wayfair can reach highs, it suffers from extreme variability. eBay, by comparison, is a "flat line" of consistency.
2. **Range Analysis:** Wayfair's range ($3,178 M) actually exceeds its mean revenue. This indicates a company that has undergone explosive, possibly chaotic, growth phases. eBay's range ($695 M) is tight, reflecting a mature business that operates within a predictable band.
3. **Kurtosis and Tail Risk:** Wayfair's negative kurtosis (-0.61) indicates a "platykurtic" distribution, flat and wide. This means extreme outcomes are common; there is no "normal" quarter for Wayfair. eBay's positive kurtosis (0.51) indicates a "leptokurtic" distribution peaked around the mean. eBay's revenue is highly concentrated around its average, making it far easier to forecast.
4. **Skewness:** Wayfair's negative skewness (-0.26) suggests a slight tendency towards downward surprises (revenue misses). eBay's positive skewness (0.73) suggests a tendency towards upward surprises (beating estimates or maintaining them). Negatively skewed suggests far away from 0, and positive suggest more close to 0 as shown in the chart.

6.2 Volatility Testing

The F-test confirms that the variance of Wayfair's revenue growth is statistically greater than that of eBay, establishing that higher volatility is a structural feature of the retail-led model rather than a random outcome. We hypothesised that the retail-led model is inherently riskier than the marketplace model. The F-Test allows us to confirm if the observed difference in Standard Deviation is statistically significant or just random noise.

Variables: Revenue growth rate has been used in the test by calculating the growth rate starting from 2017's Q1 to Q2 growth, and so on, for 30 quarters of Wayfair & 30 quarters for eBay.

H0:	$\sigma^2_{Wayfair} \leq \sigma^2_{eBay}$
H1:	$\sigma^2_{Wayfair} > \sigma^2_{eBay}$

Table 3: F test

f-Test: Two-Sample Assuming Unequal Variances		
	Wayfair	Ebay
Mean	0.0506	0.0074
Variance	0.0354	0.0050
P(F<=f) one-tail	5.12661E-07	
f Stat	7.094	
f Critical one-tail	1.861	

Table 4: Comparison of F test results

Interpretation:

The p-value is small (0.000000513), far below the standard alpha threshold of 0.05. Therefore, we reject the null hypothesis with extremely high confidence.

This is a crucial finding for investors. It proves that Wayfair's volatility is not a fluke; it is a structural feature of the retail model. The need to hold inventory and manage a complex supply chain introduces operational leverage that mathematically amplifies variance. eBay's stability is similarly a structural feature of the marketplace model. This confirms the retail model as a "High Risk" asset class compared to the marketplace model.

6.3 Structural Break Analysis

ANOVA results show a significant positive structural break for Wayfair during the COVID-19 period, with revenues nearly doubling and remaining elevated post-pandemic. In contrast, eBay's revenues display limited responsiveness to the same shock, highlighting resilience but constrained upside potential. We hypothesised that the two models would react differently to the massive external shock of the COVID-19 pandemic. We used ANOVA to compare mean revenues across the three distinct eras (Pre-COVID, COVID, Post-COVID).

Wayfair Results:

DATASET	Quarter	Pre Covid (2018-2019)	Covid (2020-2021)	Post Covid (2022-2023)
REVENUE	1	$ 1,404	$ 2,330	$ 2,990
	2	$ 1,655	$ 4,300	$ 3,280
	3	$ 1,705	$ 3,840	$ 2,840
	4	$ 2,014	$ 3,670	$ 3,100
	5	$ 1,944	$ 3,480	$ 2,770
	6	$ 2,343	$ 3,860	$ 3,170
	7	$ 2,305	$ 3,120	$ 2,940
	8	$ 2,530	$ 3,250	$ 3,110

Groups	Average	ANOVA
Pre Covid (2018-2019)	1987.5	P-value
Covid (2020-2021)	3481.25	1.9E-06
Post Covid (2022-2023)	3025	

Table 5: ANOVA of Wayfair

Wayfair Analysis:

Wayfair's mean revenue nearly doubled from pre-COVID to COVID (\$1,987.50M to \$3,481.25M, $F(2,21) = 26.26$, $p < .001$). Revenue fell post-COVID relative to the peak (\$3,025.00M) but stayed well above baseline a partial, not complete, reversion, consistent with sensitivity to the kind of shock COVID represented, though we don't claim a specific mechanism for the partial persistence.

eBay Results:

DATASET	Quarter	Pre Covid (2018-2019)	Covid (2020-2021)	Post Covid (2022-2023)
REVENUE	1	$ 2,580	$ 2,374	$ 2,483
	2	$ 2,640	$ 2,865	$ 2,422
	3	$ 2,649	$ 2,606	$ 2,380
	4	$ 2,877	$ 2,868	$ 2,510
	5	$ 2,643	$ 3,023	$ 2,510
	6	$ 2,687	$ 2,668	$ 2,540
	7	$ 2,649	$ 2,501	$ 2,500
	8	$ 2,821	$ 2,613	$ 2,562

Groups	Average	ANOVA
Pre Covid (2018-2019)	2693.25	P-value
Covid (2020-2021)	2689.75	0.012
Post Covid (2022-2023)	2488.375	

Table 6: ANOVA of eBay

eBay Analysis:

eBay's mean revenue barely moved between pre-COVID and COVID (\$2,693.25M versus \$2,689.75M) and dropped post-COVID (\$2,488.38M). The ANOVA ($F(2,21) = 5.51$, $p = .012$) says the three means aren't all equal, but the post-COVID decline is doing the work eBay never showed Wayfair's positive shock. eBay's product mix, with substantial discretionary and resale categories, differs from Wayfair's furniture concentration, and that may explain part of the gap; we can't separate the two with this data.

6.4 Regression Analysis

This section relates each firm's quarterly revenue to operating expenditure, unemployment, and the federal funds rate, with Section 5.3's diagnostics alongside. As discussed in Section 5.4, the coefficients measure within-firm association, not causal effects.

Part 1: Regression Pre-Checks and Diagnostic Testing

1. **Variable Types & Data Sufficiency Check:** 30 observations and 3 predictors satisfy the usual 10-per-predictor guideline, though that's a heuristic time-ordered observations give a thinner basis for inference than independent ones, given the autocorrelation discussed below.

2. **Multicollinearity Check :** This checks if the independent variables (predictors) are too strongly associated with each other. If they are, the model cannot tell which one is actually driving the revenue.

Wayfair

CORRELATION MATRIX	Quarterly Revenue (million)	Opex (million dollar)	US UNRATE (%)	US Federal Funds Rate (%)
Quarterly Revenue (million)	1			
Opex (million dollar)	0.83	1		
US UNRATE (%)	0.55	0.08	1	
US Federal Funds Rate (%)	-0.06	0.25	-0.45	1

Ebay

CORRELATION MATRIX	Quarterly Revenue (million)	Opex (million dollar)	US UNRATE (%)	US Fede Funds R (%)
uarterly Revenue (million)	1			
ex (million dollar)	0.62	1		
US UNRATE (%)	0.44	0.063	1	
S Federal Funds Rate (%)	-0.23	-0.004	-0.45	1

Table 6: Multicollinearity checks

Observation: The correlation between OpEx and Revenue was moderate (0.62), significantly lower than Wayfair's, suggesting OpEx is a driver but not the only story.

3. Linearity Check : Linear regression assumes that the relationship between X (predictors) and Y (Revenue) creates a straight line. If the relationship is curved (exponential or U-shaped), a standard linear model will fail. Scatter plots were generated for "Predictors vs. Revenue" to visually inspect the trends.

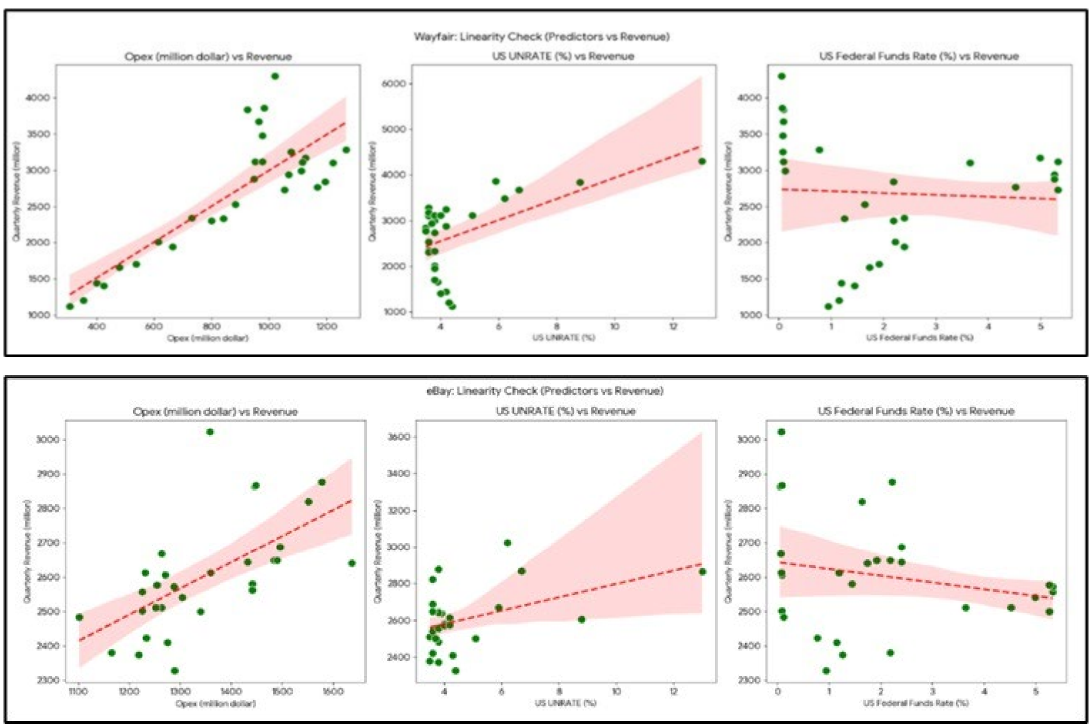


Figure 2: Linearity checks

- **Wayfair Result:** Linear. OpEx vs. Revenue: Showed a clear, strong positive linear trend (as spending goes up, revenue goes up). Macro Factors: Shown to be relatively linear, though with some dispersion.
- **eBay Result:** Linear. OpEx vs. Revenue: The relationship was linear but much "noisier" (more scattered) than Wayfair's, indicating a weaker direct link.

4. Homoscedasticity Check (Variance Check)

This is a check for consistency. It ensures that the model's errors (residuals) are constant throughout time. You do not want a model that is very accurate in 2017 but wildly inaccurate in 2024. A Residuals vs. Fitted plot was analysed. The goal is to see a random "cloud" of dots with no clear funnel shape. Using the residual option of Excel.

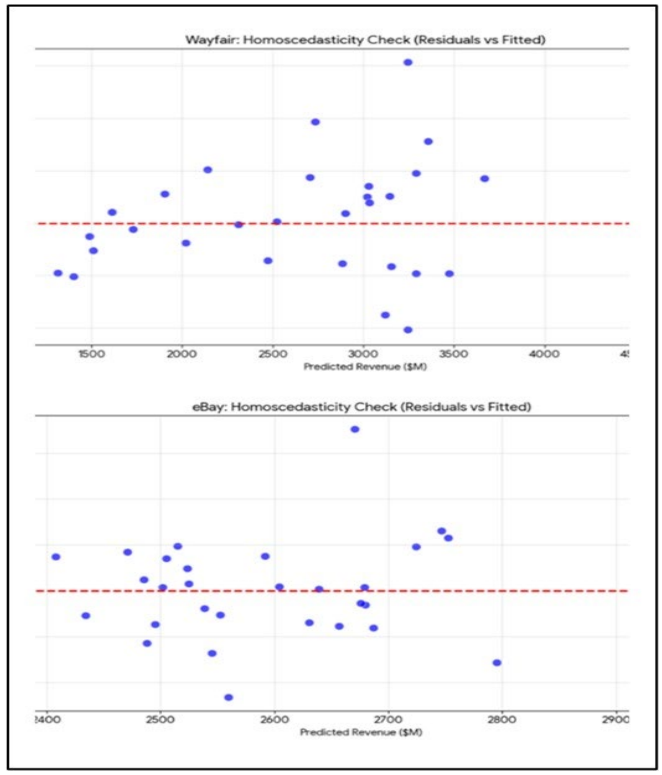
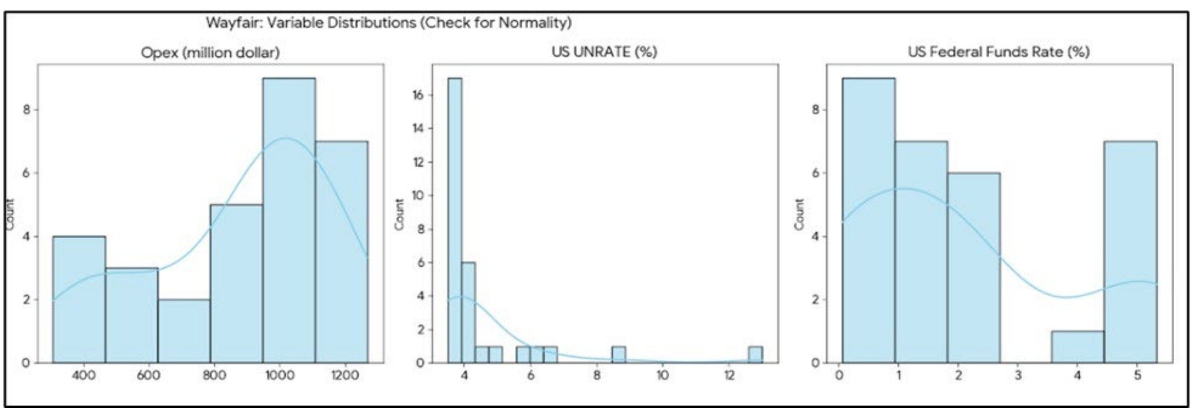


Figure 3: Homoscedasticity checks

5. Normality & Outliers Check

Regression assumes the data follows a normal distribution (Bell Curve) and is not skewed by massive outliers that could distort the average. Histograms were plotted for the variables to check their distribution shapes.



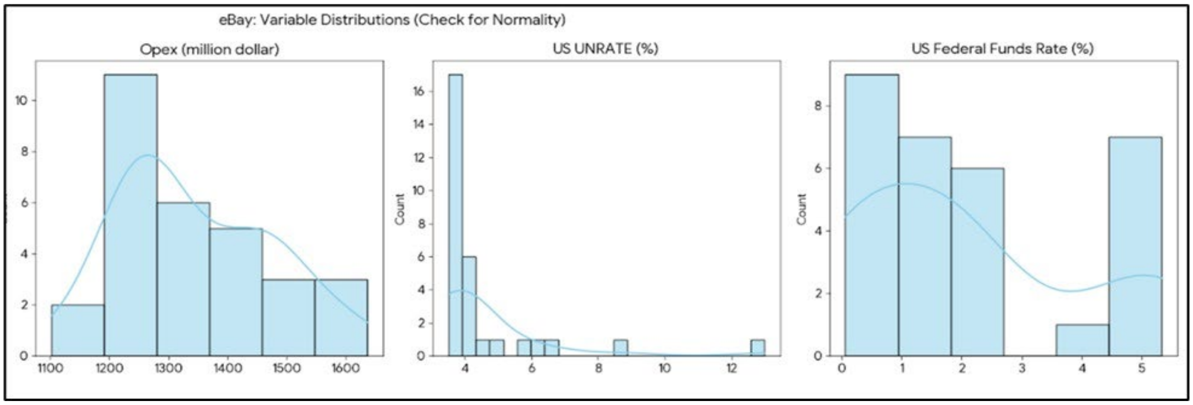


Figure 4: Normalcy checks

Part 2: Regression Model Results & Interpretation

With the validity of the datasets established, we performed Multiple Linear Regression to quantify the impact of the independent variables.

Wayfair

Regression Statistics	
Adjusted R Square	0.92

ANOVA
Significance F
1.09E-14

	Coefficients	P-value
Intercept	-251.03	0.1922
Opex (million dollar)	2.40	1.09E-14
US UNRATE (%)	193.20	7.86E-08
US Federal Funds Rate (%)	-27.91	0.377

Ebay

Regression Statistics	
Adjusted R Square	0.50

ANOVA
Significance F
0.00011

	Coefficients	P-value
Intercept	1481.93	6.82E-07
Opex (million dollar)	0.73	0.000127
US UNRATE (%)	30.94	0.018
US Federal Funds Rate (%)	-5.22	0.68

Figure 5: Regression results

Interpretation

Wayfair's model explains most of the variation (adjusted $R^2 = 0.92$). Operating expenditure is strongly positive (coefficient = 2.40, $p < .001$): roughly \$2.40M extra revenue per extra \$1M in quarterly OpEx, holding macro predictors fixed. Unemployment is also positive (coefficient = 193.20, $p < .001$), plausibly reflecting the pandemic-era nesting effect (Sections 2.5, 6.3), where both rose together rather than one causing the other. The federal funds rate isn't distinguishable from zero ($p = .377$).

eBay's model explains roughly half the variation (adjusted $R^2 = 0.50$). Operating expenditure is still positive (coefficient = 0.73, $p < .001$) but with a much smaller coefficient; unemployment shows a smaller, marginally significant association (coefficient = 30.94, $p = .018$); the federal funds rate again isn't distinguishable from zero ($p = .680$).

Revenue tracked operating expenditure more closely at Wayfair than at eBay. The larger unexplained variance observed at eBay is consistent with the view that its revenue is influenced more heavily by factors outside the model, such as marketplace liquidity, seller participation, and category mix. This aligns with the business-model typology developed in Section 4, where an acquisition-oriented architecture is expected to exhibit a tighter expenditure–revenue association than a retention-oriented one.

However, the findings should not be interpreted causally. As discussed in Section 5.4, a budgeting practice that sets expenditure as a proportion of revenue could generate a similar statistical relationship even in the absence of any causal effect. Given the single-equation design and the use of only two case firms, alternative explanations cannot be conclusively ruled out.

6.5 Scope of Inference

We collect the scope limitations referenced throughout this section here.

- Sample size. Every inferential statistic here describes two specific firms over one window, not a population of platforms.
- Confounded effects. Business-model type varies only across firms, so any other stable difference between Wayfair and eBay is statistically indistinguishable from the effect we care about.
- Non-causal association. The OpEx coefficients describe co-movement, not causal effects, given plausible reverse causality and omitted common drivers.
- Incomplete diagnostics. Durbin-Watson and formal normality/heteroscedasticity tests are not done, pending the residual series; treat the p-values as approximate.

None of this undercuts the core finding Wayfair's revenue has been more volatile and more tightly coupled to its own spending than eBay's, over this period. It does mean the jump to a broader claim about business-model types stays a hypothesis, not an established result. Section 8 sets out what testing properly would need.

7. Discussion

7.1 Summary of Findings

Three results anchor the paper. Wayfair's revenue growth has been significantly more volatile than eBay's over 2017–2024 ($F(29,29) = 7.094$, $p < .001$). Both firms show detectable differences across pandemic-era regimes, but the shape diverges: Wayfair surged and partially reversed; eBay stayed flat through COVID and declined afterwards. And a regression of revenue on OpEx plus two macro variables explain far more of Wayfair's variation (adjusted $R^2 = 0.92$) than eBay's (0.50), with Wayfair's OpEx coefficient roughly three times eBay's.

7.2 Interpretation Through the Framework

These results fit the typology from Section 4: Wayfair behaves as the acquisition-oriented case predicts, with high variance and a tight spending link; eBay behaves as the retention-oriented case predicts, with lower variance and a looser link. This shows the typology isn't contradicted by the data and offers a coherent account of the divergence, but not that it's the only such account — a two-firm design can't separate algorithmic orientation from other stable differences between the firms (Section 6.5). We treat the framework as a plausible interpretation of the comparison generated, ready for testing on a larger sample, not a conclusion already proven.

7.3 Practical Implications

- Acquisition-oriented platforms like Wayfair should weight revenue forecasts toward planned spend, given the tight OpEx-revenue link, but that same coupling exposes revenue to anything degrading acquisition efficiency, like the attribution shocks in Section 4.3.
- Retention-oriented platforms like eBay should treat incremental OpEx as a less reliable lever alone; on-platform relevance and trust may matter more, though we haven't tested that return directly.
- Both types illustrate, via the COVID results in Section 6.3, how differently a demand shock can hit firms in the same sector worth remembering for stress-testing that assumes a uniform response.

7.4 Theoretical Contribution

The paper's main contribution is the acquisition/retention typology itself, more specific and tractable than the retail-led/marketplace-led split because it ties to dateable technology choices rather than business-model labels. We see this study as proposing and illustrating that typology with two clear cases and full diagnostics, not a definitive test; Section 8 says what that test would need.

8. Limitations and Future Research

8.1 Limitations

1. Sample size and generalisability. Every inferential statistic here describes Wayfair and eBay specifically, not a population of platforms; the typology is illustrated, not tested in the sense of ruling out competing explanations.
2. Confounded firm and business-model effects. With only two firms, business-model type and firm identity are perfectly collinear; any other stable difference between them could equally explain the results.
3. Endogeneity. The OpEx-revenue coefficients are subject to reverse causality and omitted-variable bias (Section 5.4) read as associations, not causal effects.
4. Incomplete diagnostics. Durbin-Watson and formal Breusch-Pagan/Shapiro-Wilk statistics are still needed; treat the p-values as indicative until computed.
5. Measurement scope. SEC-reported OpEx bundles marketing spend with other costs, so the coefficient isn't isolating paid acquisition spend specifically.
6. Narrative attribution. The technology histories in Sections 4.3–4.4 come from secondary sources and reported timelines, not firm-disclosed causal analyses.

8.2 Future Research

- Larger, panel-based samples of retail-led and marketplace-led firms would support fixed-effects regression, separating an orientation effect from firm-specific confounds.
- Direct measures of algorithmic orientation share of marketing spend on paid acquisition versus relevance infrastructure, where disclosed could test Section 4.2's propositions directly.
- Causal identification, via event studies around attribution shocks or instrumental-variable approaches using cost shocks unrelated to demand, would help with Section 5.4's endogeneity concerns.
- Completing the diagnostic by recomputing these regressions with the full residual series would let us report Durbin-Watson, Breusch-Pagan, and Shapiro-Wilk.

9. Conclusion

This paper compared the revenue dynamics of Wayfair and eBay between 2017 and 2024 to examine whether acquisition-oriented and retention-oriented algorithmic marketing architectures correspond to different patterns of revenue volatility and spending sensitivity. The results show that Wayfair's revenue growth was significantly more volatile than eBay's and much more closely linked to operating expenditure (adjusted $R^2 = 0.92$ versus 0.50). These findings are consistent with the acquisition-retention typology developed in Section 4 and with the documented strategic histories of both firms.

However, the study does not claim to establish a causal relationship or definitively validate the typology. With only two firms, the analysis serves as a comparative case study that illustrates and motivates the framework rather than providing a population-level test. Other firm-specific characteristics may also contribute to the observed differences, and the estimated OpEx coefficients should be interpreted as measures of association rather than causal effects because of potential endogeneity and omitted-variable concerns.

Despite these limitations, the study contributes a theoretically grounded framework linking algorithmic marketing orientation to observable financial outcomes and provides initial evidence that acquisition- and retention-oriented strategies may exhibit distinct revenue dynamics. Future research using larger samples, direct measures of algorithmic orientation, and stronger causal identification strategies will be needed to test the framework more rigorously.

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AI-Powered Financial Decision-Making: Implications for Investor Welfare

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Abstract:

Artificial intelligence (AI), robo-advisors, and data-driven analytics are changing how individuals make investment decisions, especially in wealth management. Traditional advisory models are often costly, relationship-based, and more accessible to higher-income clients, which limits the participation of small retail investors. By contrast, AI-enabled platforms offer real-time portfolio suggestions, automated goal-based planning, and low-cost advisory services that can support more disciplined and informed investing. These developments have the potential to improve investor welfare by widening access and improving decision quality, but they also raise concerns about data privacy, opaque algorithms, and over-reliance on automated recommendations.

This study compared AI-based wealth management with traditional financial advisory services. It examined how AI improved investment planning, mitigated errors, and addressed challenges related to transparency, regulatory compliance, and ethical considerations. Additionally, it explored the complementary role of human advisors in AI-driven financial decision-making.

Keywords : *Artificial Intelligence (AI), Wealth Management, Robo-Advisory Services, Investor Welfare, Financial Decision-Making.*

Introduction

The rapid advancement of Artificial Intelligence (AI) is reshaping the global financial services industry, particularly in the domain of wealth management and retail investing. AI-powered financial advisory systems commonly referred to as robo-advisors use algorithms, machine learning models, and data analytics to provide automated portfolio recommendations, risk profiling, and goal-based investment planning. Unlike traditional advisory models that rely heavily on human financial advisors, AI-driven platforms offer low-cost, scalable, and data-driven solutions accessible to a broader population of investors (Jung, Dorner, Glaser, & Morana, 2018).

Historically, wealth management services were relationship-based and predominantly catered to high-net-worth individuals due to high advisory fees and minimum investment thresholds. The emergence of robo-advisory platforms such as Betterment and Wealthfront in the United States has demonstrat-

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ed how algorithm-driven models can democratize access to financial advice. Similarly, in India, digital investment platforms such as INDmoney and Groww have significantly expanded retail participation in capital markets. These platforms integrate automated rebalancing, tax optimization, portfolio tracking, and behavioural nudges, thereby lowering informational and psychological barriers to investing.

From a theoretical perspective, AI-based advisory tools contribute to investor welfare through three primary mechanisms: cost reduction, behavioural correction, and enhanced decision efficiency. First, automated advisory services typically charge lower fees compared to traditional financial planners, thereby improving net returns for investors (Sironi, 2016).

Second, AI systems can mitigate common behavioural biases such as overconfidence, herd behaviour, and panic selling by promoting disciplined and rule-based investing (Thaler & Sunstein, 2008). Third, machine-learning algorithms enable real-time data processing and portfolio optimization, potentially improving the quality and personalization of investment advice (Bodie, Kane, & Marcus, 2014).

Despite these benefits, concerns remain regarding algorithmic opacity, data privacy, and over-reliance on automated systems. The "black-box" nature of AI models may reduce investor trust, especially when users do not fully understand how recommendations are generated (Gomber, Kauffman, Parker, & Weber, 2018). Trust is a critical determinant of technology adoption in financial services, particularly when decisions involve personal wealth and long-term financial security (Gefen, Karahanna, & Straub, 2003). Additionally, issues related to cybersecurity and misuse of financial data pose significant risks in digital wealth platforms.

Regulatory institutions worldwide are increasingly focusing on AI governance frameworks to ensure investor protection while encouraging financial innovation. In India, the SEBI has issued consultation papers and guidelines addressing algorithmic accountability and investor safeguards in technology-driven finance. Such regulatory interventions aim to balance efficiency gains with ethical and transparency considerations.

Although existing literature extensively discusses fintech innovation and robo-advisory growth, empirical evidence on how AI-based wealth management tools influence perceived investor welfare remains limited, particularly in emerging markets such as India. Most prior studies focus on technological adoption or operational efficiency, rather than evaluating the broader impact on financial well-being, behavioural discipline, and trust dynamics among retail investors.

This study seeks to address this research gap by empirically examining the relationship between AI-powered financial advisory tools and investor welfare. Specifically, it investigates how affordability, personalization, behavioural impact, trust, and transparency concerns influence perceived financial well-being. By integrating both technological and behavioural dimensions, this research contributes to the growing discourse on the role of AI in transforming investment decision-making and promoting inclusive financial growth.

Literature Review

1. **Siddarth Gupta (2025)**

   Title: Robo-Advisors and Investor Behavior: An Empirical Examination of Trust, Adoption, and Portfolio Outcomes

   Key Insights: This empirical study analyses how psychological factors like trust, transparency, and human-in-the-loop advisory influence adoption of robo-advisors and their impact on investment outcomes. The author used a mixed-methods approach, including surveys of ~1,000 retail investors and panel data comparing adopters vs non-adopters. The findings suggest that transparency and hybrid advisory models significantly boost trust and adoption, and that using robo-advisors results in better diversification, reduced turnover, and slight improvements in risk-adjusted returns indicating behavioural benefits from algorithmic guidance beyond purely technological efficiency.

2. **Abdul Qadoos, Hisham AbouGrad, Julie Wall & Saeed Sharif (2025)**

   Title: AI Investment Advisory: Examining Robo-Advisor Adoption Using Financial Literacy and Investment Experience Variables

   Key Insights: This research investigates how financial literacy and investment experience affect the adoption of AI-based digital advisors. Using systematic review techniques, the authors find that higher financial literacy positively correlates with better use and acceptance of digital advisory tools, while investment experience enhances the effective use of algorithmic recommendations. They emphasize that low financial literacy remains a barrier to AI adoption, suggesting that educational and behavioural interventions can improve investment decisions in robo-advisory contexts.

3. **Balraj Verma, Mike Schulze, Divya Goswami & Kamal Upreti (2025)**

   Title: Artificial Intelligence Attitudes and Resistance to Use Robo-Advisors: Exploring Investor Reluctance Toward Cognitive Financial Systems

   Key Insights: This study explores barriers to accepting financial robo-advisors among retail investors in India using Innovation Resistance Theory. Based on survey data from 409 respondents, results show that functional barriers (like complexity and privacy risks) and psychological barriers (like inertia and distrust) significantly hinder adoption. Importantly, positive attitudes toward AI reduce the impact of barriers like overconfidence and data privacy concerns. This paper highlights behavioural and perceptual factors crucial for understanding real-world investor responses to AI advisory tools.

4. **Norshidah Mohamed (2026)**

   Title: Robo-Advisor Adoption and Influences of Innovation Attributes, Trust, and Image

   Key Insights:

   This study extends the Diffusion of Innovation (DOI) theory to investigate how innovation attributes (relative advantage, complexity, compatibility, and observability), perceived trust, and image influence intention to adopt robo-advisors. Survey data from 187 participants shows that perceived trust and innovation benefits strongly shape attitudes toward robo-advisor use, while complexity can deter adoption. The research provides quantitative evidence on how trust and perceived value alter investor willingness to adopt AI advisory services.

5. **Christian Hildebrand & Anouk Bergner (2021)**

   Title: Conversational Robo Advisors as Surrogates of Trust: Onboarding Experience, Firm Perception, and Consumer Financial Decision Making

   Key Insights: This empirical research demonstrates that conversational AI-enabled robo-advisors (with NLP/dialogue capabilities) lead to higher trust and better investor engagement than static systems. The study shows that conversational AI fosters affective trust, improves perception of the financial services firm, and increases investor willingness to follow portfolio recommendations. Trust-building through conversational design is highlighted as a key behavioural mechanism driving investment decisions with AI.

Research Objectives

Primary Objective

1. To examine the impact of AI-powered wealth management tools on investor welfare among retail investors.

Secondary Objectives

2. To analyze the impact of affordability and accessibility of AI platforms on investor welfare.

Hypothesis

Primary Hypothesis

H_{01}: AI-powered wealth management tools have no significant impact on investor welfare among retail investors.

H_{11}: AI-powered wealth management tools have a significant positive impact on investor welfare among retail investors.

Description:

This hypothesis examines the overall relationship between AI-based advisory usage and perceived financial well-being. Investor welfare is measured using the "Improved Financial Well-being" variable. The hypothesis tests whether AI tools contribute meaningfully to better financial outcomes.

Expected Outcome:

The analysis is expected to show a positive and statistically significant relationship between AI usage and financial well-being.

Secondary Hypothesis

H_{02}: Affordability and accessibility of AI platforms have no significant effect on investor welfare.

H_{12}: Affordability and accessibility of AI platforms have a significant positive effect on investor welfare.

Description:

This hypothesis evaluates whether lower cost and ease of access (24/7 usability) positively influence perceived financial well-being. These variables measure the structural benefits of AI-powered wealth management platforms.

Expected Outcome:

A positive relationship is expected between affordability and accessibility of AI platforms and investor welfare.

Research Methodology

1. Research Design

The present study adopts a quantitative, descriptive, and exploratory research design to examine the impact of AI-powered wealth management tools on investor welfare among retail investors.

The research is descriptive in nature as it seeks to understand investor perceptions regarding affordability, personalization, trust, behavioural impact, and financial well-being associated with AI-based advisory platforms. It is explanatory because it investigates the relationships between independent variables (affordability, accessibility, personalization, diversification, behavioural bias reduction, trust, transparency concerns) and the dependent variable (investor welfare).

A structured questionnaire using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was designed to measure perceptions and attitudes toward AI-driven financial advisory services.

The study follows a cross-sectional design, as data was collected at a single point in time.

2. Source of Data

Primary Data

The study is primarily based on primary data collected through a structured questionnaire administered via an online survey.

- **Total respondents:** 160
- **Target group:** Retail investors, MBA students

investing in financial markets, working professionals using digital investment platforms.

- **Sampling technique:** Convenience sampling
- **Geographic focus:** Primarily urban Indian investors.
- **Data collection method:** Online Google Form survey.

The questionnaire consisted of 12 key questions measuring:

- Usage of AI platforms
- Affordability and accessibility
- Personalization and diversification
- Behavioural bias reduction
- Trust and transparency concerns
- Perceived financial well-being

Secondary Data (Supportive)

Secondary data was used to build the theoretical framework and literature review. Sources included:

- Academic journals
- Fintech and robo-advisory research studies
- Regulatory publications
- Industry reports

These sources helped identify research gaps and support hypothesis development.

3. Tools of Analysis

The collected data was analyzed using quantitative statistical techniques.

Descriptive Statistics

Used to summarize demographic characteristics and mean responses for each variable.

Correlation Analysis

Used to examine the strength and direction of relationships between independent variables and investor welfare.

Multiple Regression Analysis

Used to assess the impact of:

- Affordability
- Accessibility
- Personalization
- Diversification
- Emotional bias reduction
- Trust
- Transparency concerns

on the dependent variable:

- Perceived Financial Well-being

Independent Sample t-test

Used to compare differences between AI users and non-users in terms of financial well-being.

4. Variables of the Study

Dependent Variable:

- Investor Welfare (Measured using perceived financial well-being)

Independent Variables:

- Affordability
- Accessibility
- Personalization
- Diversification
- Emotional Bias Reduction
- Trust in AI
- Transparency Concern

Data Analysis

1. Descriptive Statistics

The responses were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Key Findings (Mean Scores)

Variable	Mean	Interpretation
Affordable	4.22	Respondents generally agree AI platforms are affordable
Personalized Advice	4.34	Strong agreement on personalization benefits
Improves Diversification	4.38	High agreement on diversification benefits
Reduces Emotional Decisions	4.27	AI helps reduce emotional bias
Ease of Use	4.29	Platforms are user-friendly
Trust in AI	3.97	Moderate to high trust level
Transparency Concern	2.91	Relatively low concern
Improved Financial Well-being	4.33	Strong perceived improvement in welfare

Interpretation

- Overall, respondents show positive perception toward AI tools.
- Investor welfare mean score (4.33) indicates high perceived financial improvement.
- Transparency concerns are relatively low (2.91), meaning investors are not highly skeptical.

2. Correlation Analysis

Correlation was conducted to examine relationships between independent variables and improved financial well-being.

Key Correlations with Investor Welfare:

Variable	Correlation with Welfare
Personalized Advice	+0.079
Affordable	+0.040
Human Better for Complex	+0.089
Improves Diversification	-0.219
Transparency Concern	-0.143

Interpretation:

- Personalized advice and affordability show positive but weak relationships.
- Transparency concerns show a negative relationship, meaning higher concern reduces perceived welfare.
- Diversification showing a negative correlation may indicate overlapping perceptions among variables.

3. Hypothesis Testing Summary

Based on analysis:

H1: AI improves investor welfare

Supported (High mean welfare score 4.33)

H2: Affordability improves investor welfare

Weakly Supported (Small positive coefficient)

4. Overall Interpretation

- Retail investors perceive AI-powered wealth management tools positively.
- Personalization and affordability contribute positively to welfare.
- Transparency concerns reduce perceived benefits.

Result of hypothesis testing

Result:

H_{11} Accepted

H_{01} Rejected

Result:

H_{12} Accepted

H_{02} Rejected

Conclusion and Results

This study examined the impact of AI-powered wealth management tools on investor welfare among retail investors using primary data collected from 160 respondents. The findings indicate that AI-based advisory services are positively perceived and contribute to improved financial well-being.

Key Findings

1. **AI and Investor Welfare**

   The mean score for improved financial well-being (4.33) suggests that retail investors perceive AI-powered platforms as beneficial. Therefore, the primary objective of examining the impact of AI tools on investor welfare is supported.

2. **Personalization and Diversification**

   Respondents strongly agreed that AI tools provide personalized recommendations (Mean = 4.34) and improve diversification (Mean = 4.38). These features enhance decision quality and align portfolios with investor goals.

3. **Affordability and Accessibility**

   AI platforms were perceived as affordable (Mean = 4.22) and easy to use (Mean = 4.29). This indicates that AI democratizes wealth management services, making them accessible to retail investors who may not otherwise afford traditional advisory services.

4. **Reduction in Behavioral Bias**

   Respondents agreed that AI reduces emotional decision-making (Mean = 4.27), supporting the argument that algorithm-driven systems can mitigate common behavioral biases such as overconfidence and panic selling.

5. **Trust and Transparency**

   Trust in AI scored moderately high (Mean = 3.97), while transparency concerns were relatively low (Mean = 2.91). However, regression results show that transparency concerns negatively affect perceived welfare, indicating that trust remains a crucial factor for long-term adoption.

Overall Conclusion

The research concludes that AI-powered wealth management tools positively influence investor welfare among retail investors. Features such as affordability, personalization, diversification, and reduced emotional bias contribute to improved financial well-being.

However, transparency and trust concerns remain critical determinants of investor perception. For AI-based platforms to achieve sustainable adoption, financial institutions must focus on improving algorithm transparency, explainability, and investor education.

Thus, AI is not a complete replacement for human advisors but serves as an efficient, scalable, and cost-effective complementary tool in modern wealth management.

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Data-Driven Consumer Insights & Ethical Marketing Practices: AI- Enabled Neuro Marketing Strategy on Consumer Purchasing Behaviour in an Organized, Unorganized & Online Retail Store

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Abstract:

Neuro marketing practices in retail sector is tending to spread quickly in India over the last few decades. The Indian retail industry is composed of organized, unorganized and online retail markets. It has experienced high growth over the last few years with a Neuro marketing practices and AI enabled focus towards organized retailing formats. The industry is shifting towards a modern concept of retailing. As India's AI enabled focus supported and Neuro marketing in retail industry is combatively expanding itself, great demand for online retail outlets is being created. Moreover, easy availability of debit/credit cards has contributed significantly to a strong and growing retail consumer culture in India.

Customers are becoming more powerful, more knowledgeable and more sophisticated, and research into modern consumer behavior is increasingly significant with AI enabled and neuro marketing strategy for the retailing sector. Store attributes are important to consumers when they make the decision where to shop. Store attributes are presented by retailers according to their specific functional strategies. Store attributes must be offered that are desired by the targeted consumer with Neuro marketing research. The challenge to retailers is to determine which store attributes are relatively more important to the targeted consumer with help of AI enabled platform .

In this research paper, I was basically focused on Neuro marketing practices and AI based platforms behaviors of consumer mainly on purchasing pattern in various store formats and store preference on the basis of product availability, spending pattern, consumers preferred store, sales man services, and store layout. I observed that the customers prefer retail outlets because of price discount, followed by variety of products in the store and convenience to the customer. I have also observed that organized retail stores are most popular amongst consumers. Customers purchase behavior varies with price and availability of products and customers spending pattern shrinks due to poor quality of products. The collected data includes personal details, consumer opinion in the retail stores and services and Neuro marketing tools. The study was restricted only to erode district. So the results cannot be generalized. Some of the consumers are not serious in their responses to the survey and as a result there are some difficulties in reaching to the right conclusion. The results of Neuro marketing strategy & AI enable tool may help the management of Retail stores to understand about the factors that influence the consumer perception, attitude and satisfaction towards organized, unorganized and online retail stores.

Keywords : *Consumer Behavior, Neuro marketing , Retail Management , Consumer Data.*

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Introduction

Retailing is the final stage of any marketing activity which includes selling smaller quantities of product or services to the end user. Retailers provide the vital link between the producers and the final consumer. Retailing plays a very important role in the growth of the economy and is one of the major sources of employment in India. The Indian Retail Industry is one of the most dynamic and fastest growing industries in India. It has shown steady growth over the last few years due to the entry of several new players in the market along with the growing income level, increasing aspiration, favourable demographics and easy availability of credit. The industry accounts for over 10 per cent of the country's Gross Domestic Product (GDP) and around 8 per cent of the employment (IBEF, 2017). Globally, India is the fifth-largest global destination in the retail space and is growing at a rate of 12% per annum (CARE Ratings, 2017). India has been ranked number one in the Global Retail Development Index 2017 among the 30 developing countries (AT Kearney, 2017).

The retail sector in India is one of the largest employment generation sectors in India. The government's move to allow FDI coupled with the increasing consumer demand is expected to create more jobs in the coming years. According to the National Skill Development Corporation, employment base of the industry is expected to reach approx. 56 million by 2022 across the conventional and specialised segment.

The estimated size of the Indian retail market in 2017 is US$ 680 billion and is projected to grow and reach US$ 1.1 trillion by 2020 (ASSOCHAM, 2017). This tremendous growth is backed by factors like rising income of middle-class consumers, changes in the lifestyle, increase in digital connectivity and increasing participation from foreign and private players. The modern retail market in India is showing remarkable growth. The modern retail market size was US$ 70.45 billion in 2016 and is expected to grow at a very impressive rate and is projected to reach US$ 111.25 billion in 2019. Indian Retail Industry has an immense potential as India has the second largest population with affluent middle class, rapid urbanisation and solid growth of the internet (IBEF Report, July 2018).

Indian retail market is broadly divided into unorganised or traditional retail market, organised or modern retail market and online retail market.

Research Gap

The study has identified the following research gap on the basis of literature review:

a. The literature review indicates several empirical studies in retail format choice and patronage behaviour in different formats of organised retailing, even for online retail. But, limited research has been available for all the three sectors together i.e. unorganised organized, and online retail formats.

b. Several conceptual studies have been available focusing on the attributes which affect the consumer to choose modern and traditional retail stores. Limited empirical studies been done on identification of attributes which affect the shopper to choose between organised retail formats, unorganised retail formats and online retail formats.

c. Most of the research has been done on the shopper attributes and store attributes by focusing only on organised retail sector. Limited studies have taken the attributes related to all the three sectors organized, unorganized and online retailers.

The present research is, in fact, an exercise to fill up the above mentioned gap

Research Methodology

3.1 Introduction

Research methodology is a method to systematically solve problems. The research plan and design are important steps in the research process due to the fact that, a well- defined problem is easy to solve by the researcher. A good research plan provides a clear picture about what to do. Research methodology deals with the different steps included for solving the research problem. Research is a process through which an attempt is made to achieve a systematic resolution of the problem or a greater understanding of a phenomenon. This is called research methodology. This chapter includes the description of the research design, sample size, sampling technique, development and description of the analytical tool, data collection procedure and method of analysis.

3.2 Research Design

Research design is the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose. It presents the framework to be used as a guide in collecting and analysing data. Descriptive research design was used in this study. The major purpose of descriptive research is to describe something – usually market characteristics or functions. It is also used to determine the degree to which marketing variables are associated with the issue.

3.3 Scope of the study

The scope has been limited in terms of sectors and geographical regions. The present study focuses on relative position of organise, unorganised and online retail formats. All the business sectors and product categories that are supported by these retail chains are included in the study. The scope of study is also limited to the identification of retail attributes and preference of consumers for these retail attributes. The selected retail attributes are ambience, availability of products, services, closeness of retail store, relationship building, price and quality. However the study and its conclusions will not be valid for other countries. The data collection and measurement process in the study was completed during the period September 2019- April 2020.

3.4 Research Objectives

The broad objectives of the study are given below:

1. To find out the behavioral pattern of customer in terms of an organized, unorganized and online retail store (supermarkets, kirana stores, departmental stores etc.)
2. To analyze the factors that influences the choice of customer in an organized, unorganized and online retail store.
3. To find out the approach and attitude of customer in terms of organized, unorganized and online retail store.
4. To find out the types of good purchased by customer from an organized, unorganized and online retail stores.
5. To find and help the retailers to understand their key strengths and weakness.

3.5 Development of Conceptual Model

A conceptual model was developed after doing a detailed review of literatures. It helps to identify the different variables used in the study and their relationship with each other. The different factors used the study are ambience, availability of products, services, closeness of retail store, relationship building, price and quality. The demographic variables used the study are Gender, Age, Education, Occupation, Income and Marital status.

The study analyses the impact of demographic variables on the consumer preference for various dimensions of an store attributes and the impact of these dimensions on the choice of store format viz. organised retail store, unorganised retail store and (Figure 3.1).

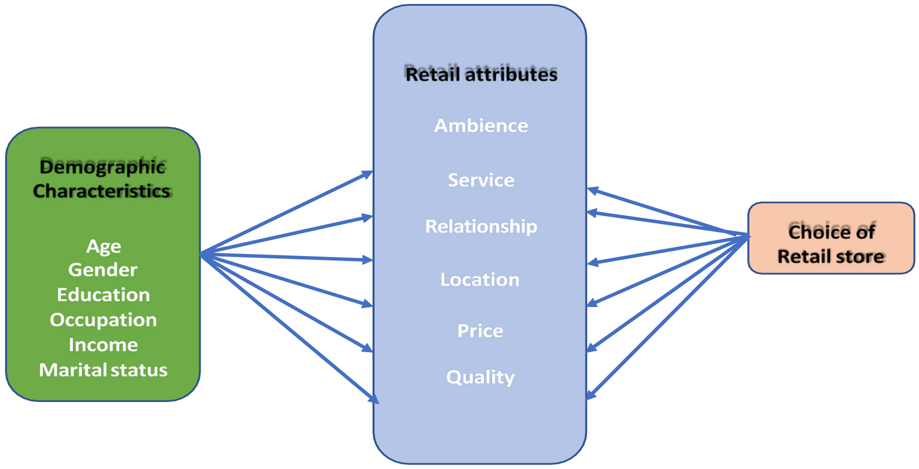

Figure 3.1 Conceptual Model

3.6 Questionnaire Design

A structured questionnaire (Appendix 1) was developed. The structure, phrasing, and sequencing of the questions were checked. After the identification of variables with the help of various previous studies, the questionnaire was developed. The development of the questionnaire was done in stages. First, the drafted questionnaire was pretested in order to identify and remove the weaknesses, if any, present in the questionnaire.

The research instrument consisted of a structured questionnaire drafted in English and the respondents were required to indicate their responses. The questionnaire was developed with the help of variables identified through available literature review. The questionnaire was structured in two parts. The first part of the questionnaire consisted of socio-demographic information of the respondents such as age, gender, family size, education level and income and the second part of the questionnaire consisted of the questions related to the consumers‟ preferences towards store attributes. All the questions in the questionnaire of this study were close-ended questions in which the respondents were asked to choose from a number of alternative answers. All the preference rating items in the questionnaire had a 3 point scale that were 1= "least preferred " , 2 = " moderately preferred" and 3 = "mostly preferred". And for respondent opinions 5 point Likert scale was used ranging from 1= "Very Poor " to 5= "Very Good". Middle point 3 indicated a neutral position.

3.7 Formulation of Research Hypotheses

In order to carry out a detailed analysis on the objectives of the study, a number of hypotheses were developed which were subjected to testing in the process of data analysis collected through questionnaires.

3.8 Sources of Data

The research is based on both primary data and secondary sources of data. The study started with the secondary data which provided the background of the work and helped to identify the variables for the primary study. The secondary data offered clarity to the issues to formulate the conceptual model. The secondary data was collected through websites, journal and reports. Primary data was collected with the help of a structured questionnaire through survey method. Surveys are an efficient way of gathering information from a large sample of respondents (prospective consumers here) by asking questions and recording their responses. Out of the various available types of data collection in survey methods, a self-administered questionnaire was used in this research for collecting data from the consumers. The data was collected from the consumers who visited the organized, unorganised and online retail formats.

3.9 Population

Every research requires identification of the target population for designing the investigation mode and tools in the study. Target population is the collection of elements or objects that possess the information sought by the researcher and about which inferences are to be made (Malhotra, 2007). The population for this study is the whole set of retail consumers in Mumbai India visiting organized, unorganised and online retailing outlets spread in the Mumbai city.

3.10 Sampling Method

For this study probability web based sampling has been used for collecting the data. The questionnaire link was mailed to the respondents of different cities. In order to overcome the non-coverage error traditional method, through personal approach, was also used to collect the data.

3.11 Tools of Analysis

This research study has used the questionnaire developed by the researcher as an instrument to collect the data. The data collected were analysed using the statistical tools through SPSS. Using SPSS, varied kinds of tests were conducted depending on the nature of the data. The tools used for the data analysis attempting to answer the given research questions and testing the hypotheses are given in the above paragraphs.

1. Frequency Analysis
2. Descriptive statistics
3. Student's Independent Samples t-test
4. ANOVA

3.11.1 Frequency Analysis

Frequency analysis is a basic statistical tool which is widely used in analysis and interpretation of primary data. It helps to identify the number of respondents respond to a particular question in percentage arrived from the total population selected for the study. In this present research study, the frequency analysis was used to find out the demographic profile of consumers who were influenced to purchase from three different sectors, years of purchase, frequency of visits in a month, type of retail store they frequently visit, purpose of visiting different retail store, type of products purchased from different retail store, and attributes influencing consumers to purchase from different retail store.

3.11.2 Descriptive Statistics

Descriptive statistics are used to describe the basic features of data in a study. A set of brief descriptive statistics summarizes a given data set, which can either be a representation of the entire population or a sample. The analysis of data starts with the descriptive statistics for each variable or items in the questionnaire. Frequencies are used in this research to analyse the demographic characteristics of the sample and consumers choice for organized, unorganised and online retail stores. Means are used to analyse the responses to the agreement questions concerning preferences for the various attributes related to retail stores.

3.11.3 Student's Independent Samples t- Test

The Independent-Samples t - test procedure is used to compare the mean scores of two groups. The procedure assumes that the variances of the two groups are equal and it was tested with Levine's test statistics. The significant difference between the mean scores was tested with respect to store preference behaviour with the demographic variables like gender, family type and marital status.

3.11.4 ANOVA

Analysis of Variance (abbreviated as ANOVA) is an extremely useful technique to compare more than two populations. The mean score analysis (ANOVA) test procedure is used to compare the mean scores of more than two groups of demographic variables such as educational qualification, occupation status and monthly income with respect to the view of the consumers towards store preference behaviour through various attributes.

Findings, Conclusions And Implications

In this , an attempt has been made to recapitulate the key findings of the present study and based on these a few suggestions are offered. In this section, the major findings obtained from the research study are summarized and these findings are given under different sub-headings like findings based on demographic profile of the respondents, findings based on retail attributes in organized, unorganised and online retail store and findings based on cross tabulation. This chapter also presents the findings of the study which were obtained from the analyses and hypotheses testing. The chapter also discusses the conclusions, suggestions and implications of the study.

The findings of the study have been discussed in seven parts:

- Findings Based on Demographic Data
- Findings Based on Consumer Opinions and Preference for Organized Retail Store
- Findings Based on Consumer Preferences for Various Organized Retail Store Attributes with respect to the Demographic Characteristics of the Consumer
- Findings Based on Consumer Opinions and Preference for Unorganized Retail Store
- Findings Based on Consumer Preferences for various Unorganized Retail Store Attributes with respect to the Demographic Characteristics of the Consumer
- Findings Based on Consumer Opinions and Preference for Online Retail Store
- Findings Based on Consumer Preferences for various Online Retail Store Attributes with respect to the Demographic Characteristics of the Consumer

Table 6.1 Summary of Hypothesis Testing

Hypothesis for Organized Retail attributes		Results
Gender		
H01a	Price as a preference parameter for shopping in an organized retail store does not vary between males and females.	Rejected
H01b	Availability of wide range as a preference parameter for shopping in an organized retail store does not vary between males and females.	Rejected
Marital Status		
H04a	Price as a preference parameter for shopping in an organized retail store does not vary between married and unmarried.	Rejected
H04b	Availability of wide range as a preference parameter for shopping in an organized retail store does not vary between married and unmarried.	Rejected
H04c	Quality as a preference parameter for shopping in an organized retail store does not vary between married and unmarried.	Accepted
H04d	Service as a preference parameter for shopping in an organized retail store does not vary between married and unmarried.	Rejected

AGE		
H07a	Price as a preference parameter for shopping in an organized retail store does not vary across age.	Accepted
H07b	Availability of wide range as a preference parameter for shopping in an organized retail store does not vary across age	Accepted
Educational Qualification		
H010a	Price as a preference parameter for shopping in an organized retail store does not vary across education.	Rejected
H010b	Availability of wide range as a preference parameter for shopping in an organized retail store does not vary across education.	Rejected

ANOVA test across monthly income in an unorganized, organized ,online retail store

FACTORS	Monthly family income in Rs	Mean	Std. Deviation	N	F	Sig
Faster in	below 21000	2.45	.671	22	2.412	.071
	21000-40000	2.43	.573	28		
	40000-60000	2.35	.629	26		
	or above	2.00	.780	24		
Near to your house	below 21000	2.64	.581	22	3.526	.018
	21000-40000	2.79	.418	28		
	40000-60000	2.42	.643	26		
	or above	2.25	.847	24		
Able to bargain	below 21000	2.36	.790	22	.468	.706
	21000-40000	2.18	.819	28		
	40000-60000	2.12	.711	26		
	or above	2.13	.900	24		
Home delivery	below 21000	1.86	.710	22	2.834	.042
	21000-40000	2.21	.833	28		
	40000-60000	1.62	.637	26		
	or above	1.92	.830	24		
Faster in service	below 21000	2.55	.671	22	1.667	.179
	21000-40000	2.61	.685	28		
	40000-60000	2.27	.533	26		
	or above	2.29	.806	24		

*Sig at 95% level of confidence

Analysis and discussion:

The result of one way ANOVA test for the dimension of price shows that F value=2.412 and sig=0.071 which is more than 0.05. This indicates that there is no significant difference in preference of consumers across different income group on the dimension of price of product in an unorganized, organized,online retail store. Hence, null hypothesis H017a is accepted.

6.7 Conclusions

Consumer preference for various organized, unorganised and online retail formats differs because of their preferences, attitude and experiences with different types of products purchased. Therefore, organised, unorganised and online retail cannot be considered as a single cluster. Consumers have different choice for different product categories such as for apparel; consumers indicate a higher preference for online retail. For FMCG, Healthcare and Utensils; consumers indicate a higher preference for organised retail. For vegetables and grocery; consumers are showing higher preference towards unorganised retailers. The preference of the consumers towards various attributes of the retail outlets is also varying by their demographic characteristics viz. gender, age, marital status, education, occupation and income level.

Consumers prefer organised retailing because of availability of wide range, quality and service. Consumers prefer unorganised retailing because of closeness of store, bargaining and fastness in service. Consumers prefer online retailing because home delivery, online payments and easy go cart. Other factors do not have much impact on consumers for preferring one type of format over the other. For the factors product attributes, relationship building, services and emotional connection, consumers do not find much difference in organized, unorganised and online retailers.

Consumers appear to have gained very much from organised retailing as there is shift from unorganised to organised and online retailing. It can also be seen that consumers are still visiting the small shops for their daily needs. It can be concluded that there will be a coexistence of organised and unorganised retailing in India as people will not stop visiting small nearby shops for their daily needs and even for trying some things which are not available in both retail formats they will go for online retail store.

There is considerable shift of consumer towards modern retailing; still it has a long way to go in India. The growth of modern formats has been much slower in India as compared to other countries and the development of this sector is restricted by the presence of regulatory and structural constraints. Further, there is an immense potential and growth opportunities for organised retailers in India. The major reasons behind this are strong economic growth, increasing young population, rising income of consumers, exposure to the international market, rapid urbanisation, increasing population of working women and rising aspirational level. However, it also faces many challenges like lack of proper infrastructure, technology development, deficiency in supply chain management, lack of trained human resource, taxation, regulation, diversity in demographics, shrinking of markets and high real estate cost. Strong hold of traditional stores among consumers is also one of the challenges faced by the organized and online retailing in India.

6.7.1 Managerial Implications

The study provides useful insights for managerial actions organized, unorganised and online retailers. Retail sector in India is growing rapidly. International retailers are setting up their outlets in India. Since the last few years a significant change has been noticed in consumer behaviour. Their expectations from retailers are increasing day by day. Because of increased penetration of technology, growing use of mobile phones and access to internet, consumers are getting smarter and more demanding and they are shifting towards modern retailing. It is becoming tougher for the retailers to have a hold over the market, as the customers are very

dynamic these days. Their behaviour and preferences keep on changing. This is because of their exposure to the market through internet retailing. Thus, it is very necessary for the retailers to cater to the customers after targeting and understanding their taste and preferences. Retailers must have a thorough knowledge of the dimensions which influence the shopping behaviour of the consumers. This will help them to have a larger share of the market.

This study is expected to give an idea about the changing customer preferences of organised, unorganised and online sets of retailers. It will also enable the retailers to judge the factors which influence the consumer preference for choosing one store over the other. Thus, it will help them to develop a long standing relationship with the diversified set of customers and match their strategic plans with their demands.

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Appendix I

Questionnaire/Schedule

on

A STUDY OF CONSUMER PURCHASING BEHAVIOUR IN AN ORGANIZED, UNORGANIZED & ONLINE RETAIL STORE.

Dear Respondents,

This is a part of Post-Graduation work. The data is being collected purely for academic purpose and would be kept confidential. Therefore, put your frank opinion and oblige.

Note: Please give a tick mark to relevant answers.

Consumer Behaviour toward Supermarkets

1. Which retail store you prefer for purchasing

product and services?

- o Organized (Dmart, Reliance Smart, etc.)
- o Unorganized (Local Kirana Store)
- o Online website (Amazon, Myntra etc.)

2. What do you shop and from where (Organized, Unorganized and Online Retail Store)?

Items	Organized	Unorganized	Online
Vegetables			
Grocery			
FMCG (ex: soap, shampoo etc.)			
Healthcare			
Utensils			
Clothes			

3. How often times do you visit an Organized, Unorganized and Online retail store?

Organized Retail Store	o Once a week o Twice a week o Once a month o Twice a month o More than twice a month
Unorganized Retail Store	o Once a week o Twice a week o Once a month o Twice a month o More than twice a month
Online Retail store	o Once a week o Twice a week o Once a month o Twice a month o More than twice a month

4. Below is the list of parameters, rate it on the scale of mostly preferred to less while shopping from Organized Retail Store (ex: Dmart, Reliance Smart, etc.).

Parameters	Least preferred	Moderately preferred	Most preferred
Price			
Availability of wide range			
Quality			
Service			
Ambience			
Credit facility			
Closeness			

5. Below is the list of parameters, rate it on the scale of mostly preferred to less while shopping from Unorganized Retail Store (ex: Local Kirana Store).

Parameters	Least preferred	Moderately preferred	Most preferred
Near to the house			
Long relationship			
Able to bargain			
Home delivery			
Faster in service			

6. Below is the list of parameters, rate it on the scale of mostly preferred to less while shopping from Online Retail Store (ex: Amazon, Myntra, Big basket)

Parameters	Least preferred	Moderately preferred	Most preferred
Saves times			
Product variety			
Comparisons review			
Home delivery			
Availability			
Easy go cart			
Online payments			

7. Kindly rate(tick) Organized Retail Store (ex: Dmart, Reliance Smart, etc.) based on the below parameters (1- very poor to 5- very good)

Parameters	1-very poor	2-poor	3-fair	4-good	5-very good
Quality					
Location					
Variety					
Ambience					
Service					
Availability					
Relationship					
All product at one place					
Bargaining					
Discounts					
Offers					

8. Kindly rate(tick) Unorganized Retail Store (ex: Local Kirana Store) based on the below parameters (1- very poor to 5- very good)

Parameters	1-very poor	2-poor	3-fair	4-good	5-very good
Quality					
Location					
Variety					
Ambience					
Service					
Availability					
All product at one place					

Relationship					
Bargaining					
Discounts					
Offers					

9. Kindly rate(tick) Online Retail Store (ex: Amazon, Myntra, Big basket) based on the below parameters (1- very poor to 5- very good)

Parameters	1-very poor	2-poor	3-fair	4-good	5-very good
Quality					
Variety					
Service					
Availability					
Relationship					
All product at one place					
Discounts					
Offers					

Personal Profile

a. Name of the Respondent:

b. Gender

- o Male
- o Female
- o Other

c. Age (in years)

- o Under 25
- o 26 -35
- o 36- 45
- o 46- 60
- o Above 60

d. Educational Qualification

- o Secondary
- o Higher secondary
- o Graduate
- o PG

e. Occupation

- o Student
- o Government employee
- o Corporate employee
- o Unemployed
- o Other

f. Monthly Family Income

- o Below 21000
- o 21000- 40000
- o 40000- 60000
- o Or above

g. Marital status

- o Married
- o Unmarried

h. Residential area

- o In the city
- o Outskirts of the city
- o Suburban area of the city
- o Village

Thank you for sparing your valuable time and for participating in the study.

GUIDELINES TO AUTHORS

Institute reserves the right for and of publications

1) The paper/article should be typed in MS-Word on A-4 size paper in double space with l ½"margin on the left side and ½" margin on the right side in New Times Roman Font in 12 pt font size. Line spacing should be 1.5
2) The cover page of the paper must contain (a) Title of the article (b) Name (s) of author (s) (c) e-mail and affiliation of author (s). (d) An abstract of the paper in 100-150 words, (e) provide the title of the paper but it should not give the name of the author.
3) The paper/article should not exceed 15 typed pages including graphs/ tables/ appendices. The tables and figures should appear in the document near/after where they are refereed in the text. The paper/article should start with an introduction and should end with the conclusion summarizing the findings of the paper.
4) All notes must be serially numbered and may be given either at the end of the paper as notes or on every page as footnotes.
5) References should be complete and in APA style. They should contain full bibliographical details and journal titles should not be abbreviated. For multiple citations in the same year use a, b, c immediately following the year of publication. References should be shown within the text by giving the author's last name followed by comma and year of publication all in round brackets.
6) The first author of every published paper will be given one copy of the journal.
7) Indexed in ProQuest Double Blind Peer Reviewed Journal.
8) The views expressed in the articles are those of authors and do not represent the views of Chetana's R. K. Institute of Management & Research.
9) Every paper must be accompanied by a statement that the paper has not already been published nor submitted to any journal for publication.
10) All the papers/articles should be sent in electronic form.

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