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# Financial Reporting Quality and Labour Investment Efficiency: Role of Financial Constraint

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## Abstract

This paper seeks to understand the potential role of high financial reporting quality in affecting investments in labour in the presence of financial constraints. Analysis of 249 non-financial Indian companies listed with BSE500 from 2007-2019 shows that financial reporting quality is negatively associated with underinvestment in labour. We find that financial constraint plays a big role in defining this relationship. The relation between FRQ and underinvestment in labour is more pronounced for financially contrasted firms in our sample. These results suggest that one mechanism through which reporting quality and labour investment efficiency are linked is a reduction of market frictions that hamper efficient investment in labour. Financially constrained firms will, therefore, do better in terms of labour investment by choosing high FRQ.

**Keywords:** Financial reporting quality; labour investment efficiency; financial constraint, overinvestment; underinvestment; India

## Introduction

Despite the growing importance of labour in India's labour-intensive economy, firms continue to face significant labour investment inefficiencies, either over investing often due to rigid employment regulations, or under investing because of high informality, and managerial risk aversion (Besley & Burgess, 2004; ADB, 2017). Although reforms such as the Companies Act, 2013 and the adoption of Ind AS have improved financial reporting quality (hereafter, FRQ), little is known about whether these enhancements translate into better labour allocation decisions. Existing research in India largely focuses on FRQ's impact on capital investment, earnings management, or firm valuation (Biddle, Hilary, & Verdi, 2009; Chen, Tang, Jiang, & Lin, 2011), while studies on labour inefficiency concentrate on regulatory barriers or labour laws (Ghosh & Ghosh, 2012). As a result, there is limited evidence linking the information environment shaped by FRQ to firm-level labour investment outcomes.

International evidence on FRQ and labour investment comes primarily from developed economies with flexible labour markets, making it difficult to generalise these findings to India's institutional setting (Ghaly et al., 2020; Fazzari, Hubbard, & Petersen, 1988). Indian firms operate under persistent constraints such as uneven labour reforms, widespread use of contractual labour, and diverse governance structures, all of which affect labour adjustment decisions. Prior studies indicate that strict employment laws cause firms to delay hiring or rely excessively on temporary workers, leading to labour misallocation (Besley & Burgess, 2004; ADB, 2017). However, the role of financial reporting transparency in shaping these decisions remains largely unexplored.

Moreover, the moderating role of financial constraints in this relationship is not well understood in emerging markets. Financially constrained firms often under-invest in labour despite growth opportunities, and high FRQ may help mitigate this by improving access to credit (Francis, LaFond, Olsson, & Schipper, 2005; Fazzari et al., 1988). Empirical evidence on this interaction in India is scarce. This gap highlights the need for research examining how FRQ influences labour investment inefficiency and how financial constraints shape this relationship.

"Financial economists have long been interested in the linkages between financial frictions and firm-level investment. Within the last decade, this general interest in linkages between real and financial-economic activity has extended into the area of labour markets" (p. 539, Whited, 2019). Deviation from optimal investment increases a firm's wage bill in case of over-investment and decreases firm productivity in case of under-investment. Each of these actions affects revenue and causes greater uncertainty concerning a firm's future earnings (Jensen, 1986; Almeida and Carneiro, 2009). Becker (1962) argued that the most successful firms are those that invest in their human capital (or labour) most effectively and efficiently.

Capital markets in the real world are not perfect due to the presence of taxes, information asymmetry, agency problems, and so on. This gives rise to "financial constraints." Primarily, financial constraints occur when there is a substantial difference between the cost of raising funds externally and the opportunity cost of internal capital (Fazzari, et al., 1988; Whited, 1992; Kaplan and Zingales, 1997). As per Bhaduri (2005), a firm is defined as financially constrained if the cost (high) or non-availability of external funds refrains the firm from undertaking an optimum investment decision, which it would have taken otherwise if internal funds were available.

High FRQ is associated with greater information transparency, making the investors more informed, reducing uncertainty, and hence, eventually reducing the cost of capital, making it easier and cheaper for firms to finance labour.

Frictions in the capital market affect the hiring practices of the firm, especially when labour has a fixed or at least quasi-fixed component (Oi, 1996; Farmer, 1985; Hamermesh, 1993; Hamermesh and Pfann, 1996), with adjustment costs related to hiring, training, and firing employees. Fixed components imply that financially constrained firms will face more labour-management issues. Such constrained firms, for example, may find it hard to hoard and preserve highly trained employees even when they face only a temporary sluggish demand for their products.

In this paper, we focus on the role of financial constraints in determining the relationship between financial reporting quality (hereafter, FRQ) and labour investment efficiency (hereafter, LIE) for listed, non-financial Indian firms. We specifically wish to understand whether the relationship between FRQ and LIE depends on the specific nature of sub-optimal investment and the role of financial constraints in determining the relationship. We investigate the role of financial constraint as a moderating variable in the relationship between FRQ and labour investment inefficiency.

The paper has five sections. The next section explores the relevant literature and develops the main hypotheses. In section three, data and methodology are discussed. In section four, the results are presented and discussed. Section five concludes the paper.

## Literature Review and Hypotheses

The Classical Economic Model views labor solely as a variable factor, assuming that labor costs align perfectly with revenues and do not necessitate external financing. Within this framework, issues of information asymmetry and the quality of financial reporting (FRQ) are deemed irrelevant for decisions regarding labor investments, suggesting FRQ has no impact on

Labour Investment Efficiency (LIE). Contemporary research, however, challenges this view by highlighting that labour costs include fixed or quasi-fixed components—such as hiring, firing, and training costs—which are significant (Oi, 1962; Farmer, 1985; Hamermesh, 1993; Hamermesh & Pfann, 1996). Hiring costs involve recruitment, training, and temporary production losses (Nickell, 1978; Hamermesh & Pfann, 1996), while firing costs may include legal, union, and psychological costs. Labour investment decisions are often irreversible, especially in the short run (Lopatta et al., 2020). These fixed costs create a timing mismatch between labour expenditures and revenue generation, implying that firms may require external financing to cover labour costs. Consequently, capital market frictions affect labour investment decisions, and higher FRQ can alleviate these frictions by reducing information asymmetry and facilitating efficient financing (Greenwald & Stiglitz, 1988). Thus, FRQ plays a meaningful role in enhancing Labour Investment Efficiency when labour costs are not purely variable.

Labour investment inefficiency can arise due to underinvestment in human capital, often caused by adverse selection or information asymmetry between outside investors and managers. When investors face uncertainty about the firm's labour-related investments, they perceive higher risk and, consequently, demand higher expected returns. This risk perception leads investors to discount the prices of securities with greater uncertainty. As a result, financing otherwise profitable labour investments becomes more expensive, which can cause under-hiring or over-firing.

Firms can mitigate such information asymmetry by providing high-quality disclosures that enable investors to make rational economic decisions. By reducing uncertainty, firms that maintain transparent and informative reporting are rewarded by investors through lower required returns. This reduction in the cost of external financing facilitates efficient investment decisions, including optimal decisions regarding labour, thereby enhancing overall operational efficiency (Biddle & Hilary, 2006; Bushman, Piotroski, & Smith, 2004; Diamond & Verrecchia, 1991; Ahmed & Duellman, 2011).

High-quality financial reporting (FRQ) helps reduce information asymmetry between owners/investors and managers by strengthening external monitoring and oversight of managerial activities, thereby mitigating agency problems. Over-investment in labour may occur due to managerial moral hazard, such as self-empire building through over-hiring or under-firing—retaining employees on unprofitable or negative NPV projects. By improving transparency, high FRQ limits information asymmetry and supports managers in making more efficient labour investment decisions, ultimately enhancing firm performance (Jung, Lee, & Weber, 2014). Conversely, when financial reporting quality is low, managers are more likely to pursue empire-building strategies (Hope & Thomas, 2008).

FRQ can play a direct or indirect role in augmenting efficacious investments in human capital. Jung et al., (2014) focused on the overlooked investments in labour by examining the direct relationship between FRQ and labour investment efficiency (hereafter, LIE) for North American firms. The results were consistent with the notion that higher-quality financial reporting facilitates more efficient investments in labour, in general, and is associated with less over and under-investment. In a study based in the UK, Zhang et al. (2020) found a strong negative association between accounting comparability and abnormal net hiring. Recently, Joshi and Dey (2025) have investigated the association between FRQ and labour investment inefficiency in the context of India, suggesting that a high value of FRQ combats inefficiency in labour investment (in the form of over-investment) for Indian firms, suggesting that better FRQ acts as a disciplinary tool for better monitoring of managers.

There are various channels through which FRQ affects net hiring decisions. Ha and Feng (2018) have propounded that timely recognition of loss improves efficiency in labour investment by reducing the information asymmetry between managers and capital providers and acts as a disciplining mechanism. Jung et al. (2021) have shown that high-quality financial reporting can affect employment through credit and labour-supply channels. The credit supply-channel alleviates the information and agency problems underlying refinancing risk.

Studies have also shown that a firm's financial constraints play a role in labour investment decisions (Benmelech et al., 2021; Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Huang and Tarkom, 2022). Even though current or future investments determine firms' labour demand, firms adjust stocks slowly due to financial constraints. These findings are consistent with the argument that labour costs are not purely variable costs, hence requiring financing (e.g., Oi, 1962; Hamermesh, 1993).

High-quality financial reporting (FRQ) is crucial in reducing underinvestment in labor, especially in firms that face financial constraints. When companies have restricted access to external funding, managers may be hesitant to invest in labor due to uncertainties regarding the potential returns or due to a cautious approach to risk. Enhanced financial reporting diminishes the information gap between managers and investors, which in turn better equips investors to oversee managerial actions and improves the likelihood of securing external financing (Biddle & Hilary, 2006; Chen et al., 2011). Consequently, firms with superior FRQ are more inclined to make appropriate labor investments, even when they are financially constrained. Research findings corroborate this idea, indicating that the beneficial impact of FRQ on labor investment is more pronounced among firms that experience higher financial constraints, underlining the importance of dependable financial information in addressing underinvestment issues (Biddle et al., 2009; Ahmed & Duellman, 2011). Ben-Nasr and Alshwer (2016) have shown that more financially constrained firms are less able to invest efficiently in labour, which makes the relationship between FRQ and LIE more pronounced (Fig 1).

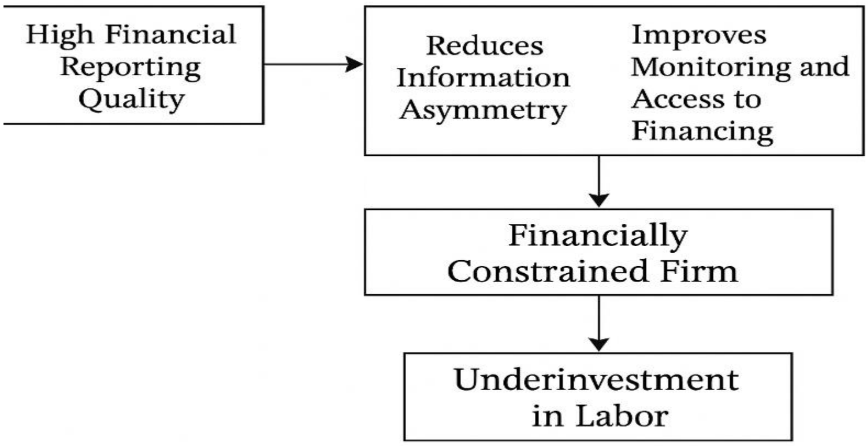


**Figure 1: Role of FRQ in combating underinvestment for firms experiencing financial constraint**

The above evidence suggests that financing constraints may play a pivotal role in determining the relationship between FRQ and firm hiring decisions. However, surprisingly, a long search of literature could not find even a single study examining this important relationship, especially for India.

Empirical evidence indicates that the relationship between financial reporting quality (FRQ) and overinvestment is stronger in firms with large cash balances and free cash flows (see Fig 2). For example, Biddle and Hilary (2006) and Biddle et al. (2009) show that high FRQ strengthens managerial monitoring, thereby influencing investment efficiency. Chen et al. (2011) and Ahmed and Duellman (2011) find that firms with abundant internal resources are more prone to overinvestment when governance mechanisms are weak, but high FRQ mitigates this tendency. Similarly, Bushman et al. (2011) document that firms with larger cash balances or free cash flows exhibit greater sensitivity to FRQ in controlling resource allocation, including labour investment. Such firms are more likely to overspend available resources, and high-quality financial reporting can play a critical role in mitigating this tendency (Jensen, 1986; Biddle et al., 2009; Chen et al., 2011).

Therefore, in order to understand the role of FRQ in mitigating abnormal net hiring, we propose the following hypotheses:
H1: Financial reporting quality is negatively associated with underinvestment.
H2: Financial reporting quality is negatively associated with overinvestment.

More importantly, we investigate the mechanisms through which FRQ affects investment efficiency using cross-sectional analysis and sub-sample analysis. Thus, we hypothesise:
H3: The relation between FRQ and underinvestment in labour is stronger when firms face higher financial constraints.
H4: The relation between FRQ and overinvestment in labour is stronger for firms holding large cash balances and free cash flows.

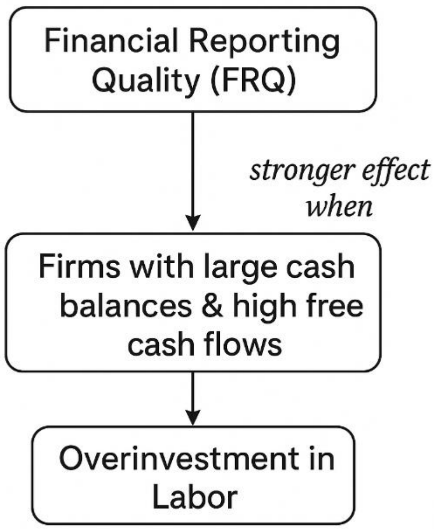


**Figure 2: Role of FRQ in combating overinvestment for firms with large cash balances and high free cash flows**

**Data Description and Analysis**

Data has been collected from PROWESS (CMIE database) from a sample of selected Indian companies from BSE500 index from 2007 to 2019. If Prowess data is missing for some company and/or year, the data has been taken from Indiastat, Bloomberg, AceEquity, moneycontrol.com, and various companies' Annual reports. All financial companies have been removed because the financial firms have an entirely different mode of investment than non-financial companies (Biddle et al., 2009). Also, the companies for which data was unavailable or those that are small, i.e., employees less than 100, have been excluded to mitigate the effect of extreme changes in labor hiring on results.

In line with prior studies, all variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The final sample consists of 3237 firm-year observations for 249 firms.

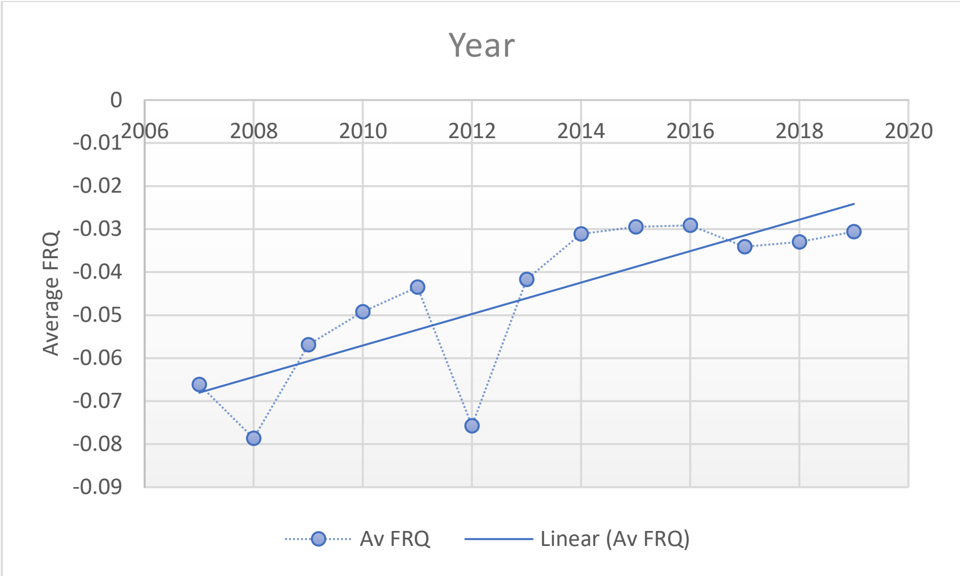


**Figure 3: Average FRQ Score (2007 to 2019)**

Figure 3 plots the evolution of the average Financial Reporting Quality (FRQ) for the sample firms over the period 2007–2019. The series exhibits a clear upward trajectory, indicating a gradual improvement in reporting quality across firms. Although the early years are characterised by moderate volatility—likely reflecting post-crisis uncertainty and heterogeneous adjustments in reporting practices—the overall direction remains positive. A pronounced decline in 2012 is followed by a sharp improvement from 2013 onwards, coinciding with the introduction of the Companies Act 2013, which substantially strengthened disclosure, governance, and enforcement mechanisms. The sustained elevation and reduced variability in FRQ values after 2014 suggest that these regulatory reforms, alongside the initial implementation of IND-AS in 2016, contributed to a structural enhancement in financial reporting practices. The positive slope of the fitted trend line reinforces the presence of a long-term improvement in FRQ, consistent with the expectation that regulatory tightening and increased monitoring promote higher-quality financial reporting in emerging market settings.

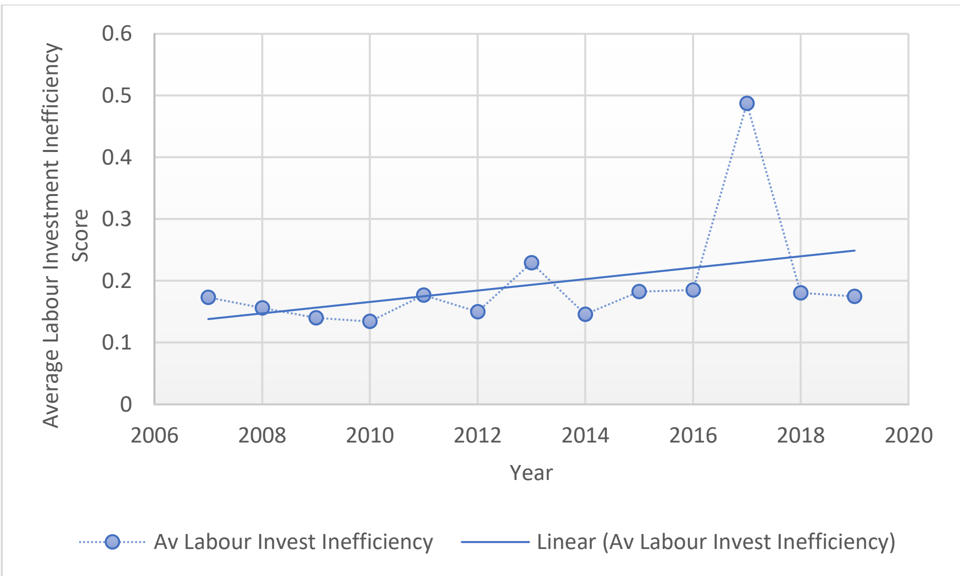


**Figure 4: Average Labour Investment Inefficiency Score (2007 to 2019)**

Figure 4 presents the temporal evolution of average labour investment inefficiency for the sample firms over the period 2007–2019. The pattern reveals relatively modest fluctuations in inefficiency levels during the early years, followed by a gradual upward trajectory over time. While the series remains centred around values between 0.13 and 0.20 for most of the sample window, a visible escalation begins after 2013, culminating in a pronounced spike in 2017. This sharp increase likely reflects transitional frictions associated with major regulatory and accounting changes—particularly the implementation of the Companies Act 2013 and the introduction of IND-AS beginning in 2016—which may have temporarily amplified firms' labour adjustment costs and misalignment between labour demand and realised performance. The slight reversion and stabilization observed after 2017 suggest partial correction of these short-term distortions as firms adjust to the new regulatory environment.

Figure 3 and 4 taken together reflects that Average FRQ rises steadily over the sample period, reflecting improvements in reporting quality following major regulatory reforms, while labour investment inefficiency exhibits a mild upward drift with a notable spike during the IND-AS transition years. Together, these trends suggest that enhanced reporting quality may coincide with short-term labour adjustment frictions, indicating a lag before transparency improvements translate into more efficient labour investment decisions.

Figure 5 compares the evolution of average FRQ for large and small firms over 2007–2019. Both groups exhibit a broadly similar upward trend, with FRQ improving steadily over time and converging after 2013. Small firms initially show marginally better FRQ, but a sharp decline around 2012–2013 is followed by rapid improvement consistent with regulatory reforms. From 2014 onward, large firms maintain slightly higher and more stable FRQ levels, suggesting stronger reporting systems and faster adaptation to regulatory changes. Overall, the trends indicate that reporting quality improved for both size groups, with large firms displaying a modest but persistent advantage.

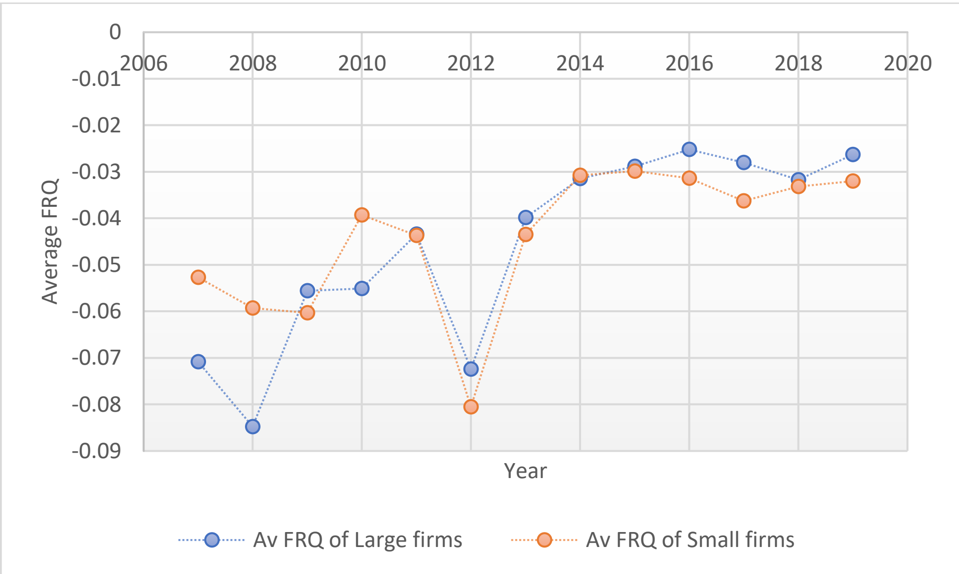


**Figure 5: Comparison of FRQ for large and small firms (2007-2019)**

To be consistent with current research reporting quality is measured using the model of Dechow and Dichev (2002), augmented with the fundamental variables from Jones (1991), as suggested by McNicholas (2002). The measure of earnings quality based on the premise put forward by Dechow and Dichev (2002) has been adopted, who argue that, among the various available proxies, this measure is most directly linked to information risk[1]. Reporting quality is measured by the extent to which working capital (denoted by *WC*) accruals match with cash flow realizations[2].

$$\Delta WC_{i,t} = \gamma_0 + \gamma_1\, CFO_{i,t-1} + \gamma_2\, CFO_{i,t} + \gamma_3\, CFO_{i,t+1} + \gamma_4\, \Delta REV_{i,t} + \gamma_5\, PPE_{i,t} + \varepsilon_{i,t+1} \qquad (1)$$

where *CFO* denotes cash flow operations, *REV* denotes revenue[3], and property, *PPE* denotes property, plant, and equipment.

In line with prior studies, we estimate the model for all industries with at least 10 firm data available in a particular year, using the NIC 2-digit industry classification (2008) to enhance comparability across industries. We then obtain the residuals from Eq. 1 and define FRQ as the negative absolute value of these residuals, such that higher values correspond to higher financial reporting quality.[4] All variables are scaled by lagged assets to reduce heteroscedasticity in Eq. 1. The Fixed-Effects Model has been employed to address fixed unobservable heterogeneity.

The labour demand model proposed by Pinnuck and Lillis (2007) has been adopted to measure labour investment inefficiency. This method is widely used in the existing literature (Jung et al., 2014; Cao and Rees, 2020; Huang and Tarkom, 2022). A firm's net hiring is measured as the percentage change in the number of employees between the year t and t-1, to proxy for investment in labour. In contrast to net hiring, conceptually abnormal net hiring or labour investment inefficiencies have been reflected as the absolute deviation of labour investment from its expected (optimal) level justified by economic fundamentals. The resultant absolute value of residuals is the measure of labour investment inefficiency.

We use Eq. 2 to determine the measure of labour investment inefficiency of the ith firm in year t.

$$Net\ Hiring_{i,t} = \beta_0 + \beta_1 SALESGROWTH_{i,t-1} + \beta_2 SALESGROWTH_{i,t} + \beta_3 \Delta ROA_{i,t} + \beta_4 \Delta ROA_{i,t-1} + \beta_5 ROA_{i,t} + \beta_6 RETURN_{i,t} + \beta_7 SIZE_{i,t-1} + \beta_8 QUICK_{i,t-1} + \beta_9 \Delta QUICK_{i,t-1} + \beta_{10} \Delta QUICK_{i,t} + \beta_{11} LEV_{i,t-1} + \beta_{12} LOSSBIN1_{i,t-1} + \beta_{13} LOSSBIN2_{i,t-1} + \beta_{14} LOSSBIN3_{i,t-1} + \beta_{15} LOSSBIN4_{i,t-1} + \beta_{16} LOSSBIN5_{i,t-1} + \varepsilon_{i,t} \qquad (2)$$

where *Net Hiring* = percentage change in employees; *SALESGROWTH* = percentage change in sales revenue; *ROA* = net income scaled by total assets; *RETURN* = EBIT scaled by lagged total assets; *SIZE* = natural log of market value of assets at the beginning of the year; *QUICK* = the ratio of cash and short-term investments plus receivables to current liabilities at the beginning of the year; *LEV* = the ratio of total borrowing to total assets at the beginning of the year; and the *LOSSBIN* variables are indicators for each 0.005 interval of prior year *ROA* from 0 to 0.025 (i.e., *LOSSBIN*1 equals 1 if prior-year *ROA* is between 0.005 and 0, *LOSSBIN*2 equals 1 if prior-year *ROA* is between 0.010 and 0.005, and so on).

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[1] Information risk reflects the uncertainty surrounding the accuracy of the information contained in firms' financial reports and is known to be priced by investors. Consequently, a measure that captures the extent to which current accruals map into future and past cash flows provides a more reliable indication of the quality of the underlying earnings process and is therefore appropriate for our analysis.

[2] Working capital accruals and cash flows pertaining to main activities are used in order to measure the accrual quality which in turn has been the proxy for FRQ. The reason to use the working capital accruals is the fact that working capital accruals generally occur within one year making both theory and empirical work more tractable. Moreover, the long lags between non-current accruals and cash flow realisations practically restrict this model to only short-term accruals. All Indian companies do follow 'Accrual Accounting System' for preparing their financial system.

3 Revenues are used to control for the economic environment of the firm because they are an objective measure of the firm's operations before manipulations made by managers. Changes in revenue and PPE have been included in order to control for non-discretionary accruals caused by changing economic conditions. Further, gross PPE are included in the model rather than changes in this account because total depreciation expenses are included in the total accruals measure.

[4] Higher value of residuals obtained from Eq1 implies lower FRQ which if multiplied by -1 represents higher FRQ.

The reason for including the level of some variables and the level of change in other variables is to control for the expected level and expected change in the variable. So, current sales growth and current *RETURN* are used as proxies for future sales growth and expected profitability. Similarly, the previous year's level and changes are included to control for the current level and change in the variable, respectively. So, $SIZE_{i,t-1}$ ,$QUICK_{i,t-1}$, $LEV_{i,t-1}$,$SALESGROWTH_{i,\,t-1}$, Loss $\text{dummies}_{i,t-1}$ have been included to control for current investment opportunities as well as financial constraints, liquidity, growth, and financial risk.

To address heteroscedasticity in the residuals, regression with controlling firm-fixed and year-fixed effects is estimated using the robust standard errors technique (Ha and Feng, 2018; Lopatta et al., 2020; Jung et al., 2016, 2021). Zero residual signifies that a firm's actual level of hiring is exactly equal to the estimated level of hiring based on various economic fundamentals. A positive residual value indicates over-investment in labour, while a negative residual value indicates under-investment in labour.

To explore the link between FRQ and labour investment inefficiency, the following regression model has been estimated:

$$|ABN\ (Labour\ Investment)\ |_{i,t} = \delta_0 + \delta_1\ FQ_{\ i,\ t-1} + \delta_2\ MTB_{i,t-1} + \delta_3\ SIZE_{i,t-1} + \delta_4\ Quick_{i,t-1} + \delta_5\ Lev_{\ i,t-1} + \delta_6\ Divi_{\ i,t-1} + \delta_7\ Std\ CFO_{\ i,t-1} + \delta_8\ Std\ Sales_{\ i,t-1} + \delta_9\ Tangible_{\ i,t-1} + \delta_{10}\ Loss_{\ i,t-1} + \delta_{11}\ Insti_{\ i,t-1} + \delta_{12}\ Std\ Net\ Hire_{\ i,t-1} + \delta_{13}\ Labour\ Intensity_{\ i,t-1} + \delta_{14}\ |AB\ Invest\ Other|_{\ i,\ t} + \varepsilon_{\ i,t} \quad \text{……………………………} (3)$$

$|\text{AB Invest Other}|_{i,\,t}$ measures the extent to which non-labour investments deviate from their expected level. Following Jung et al. (2014), variables including growth options ($\text{MTB}_{i,t-1}$), firm size ($\text{Size}_{i,t-1}$), Liquidity ($\text{Quick}_{i,t-1}$), Leverage ($\text{Lev}_{i,t-1}$), dividend pay-out ($\text{Divi}_{i,t-1}$), cash flow and sales volatility (Std $\text{CFO}_{i,t-1}$, Std $\text{Sales}_{i-t-1}$), tangibility ($\text{Tangible}_{i,t-1}$) and incidence of losses ( $\text{Loss}_{i,t-1}$) have been controlled for. Further, the potential external monitoring role of institutional owners has been considered by controlling for the proportion of outstanding shares held by institutions ($\text{INST}_{i,\,t-1}$). Finally, any indirect effect on abnormal net hiring stemming from other or non-labour investment decisions (|AB Invest Other|) has also been controlled.

To prevent problems such as heteroscedasticity in the residuals, the regression with controlling firm-fixed and year-fixed effects is estimated using the robust standard errors technique (Ha and Feng, 2018; Lopatta et al., 2020; Jung et al., 2016, 2022). Industry fixed effects have been included to control for unobservable firm heterogeneity. Year-fixed effects represent year dummies, to control for time-specific factors on a firm′s hiring. Standard errors by firm and year have been clustered to control for cross-sectional and intertemporal correlation.

## Results

### FRQ and under or over-investment

Table1 presents descriptive statistics for Eq. 3. The mean of the percentage of abnormal change in the number of employees (ABNETHIRE) is 19.4 per cent. The table also shows that Indian firms in this sample have significant growth opportunities with an average MTB equal to 4.31.

979 (2258) firm-year observations are classified as overinvesting (underinvesting). We find the residuals from the labour investment model are more frequently negative.

Figure 6 presents that Average FRQ shows noticeable improvement after the Companies Act 2013, with the post-reform period marked by higher and more stable reporting quality compared to the more volatile pre-reform years. This structural shift suggests that the

Act's strengthened disclosure, governance, and enforcement provisions had a persistent positive effect on firms' financial reporting practices.

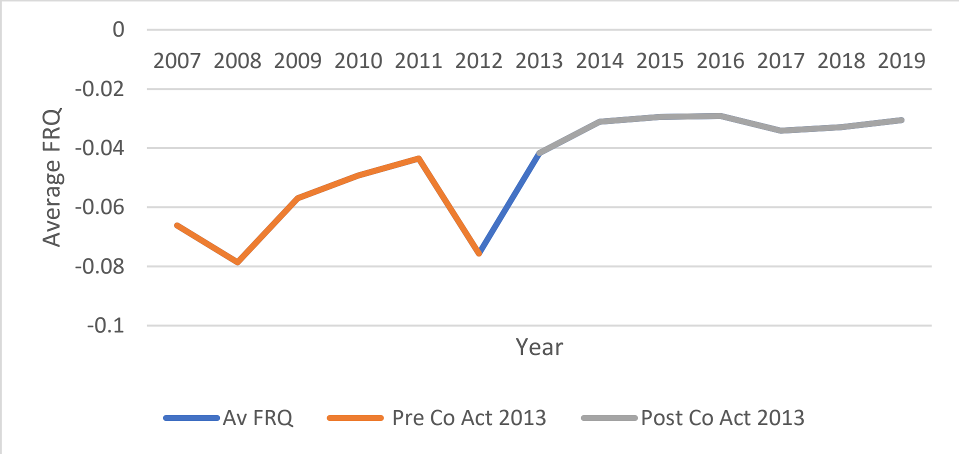


**Figure 6: Average FRQ Pre/ Post Reform Period**

Table 2 reports Pearson correlation coefficients between the variables in the abnormal net hiring. In general, the correlations between most control variables and our dependent variable align with our expectations[5].

Based on the fixed effects model statistically approved by the Hausman test, we first examine the impact of FRQ on labour investment inefficiency for sub-samples of firms based on signs of abnormal net hiring. Thus, the analysis has been done for the firms for which actual labour investment is greater than expected (i.e., over-investment) and the sub-samples for which the actual labour investment is lesser than expected (i.e., under-investment). Eq.3 has been estimated for each sub-sample and the absolute positive and absolute negative abnormal net hire have been used as the dependent variable. This enables us to examine the relationship between FRQ and either over- or under-investment separately.

As presented in Table 3 (Column 1), the relation between overinvestments in labour and FRQ was found to be insignificant, though the sign of the coefficient is negative. Such a finding is in line with the work of Ball et al. (2000), which contends that in a setting with weak investor protection and high ownership concentration, such as that of Indian firms, the weight given to accounting information for monitoring managers' activities is restricted. As a result, the governance structures of Indian firms might not rely on FRQ as a monitoring tool to mitigate overinvestment. On the other hand, the significant effect of FRQ on underinvestment (Column 2) suggests that FRQ may be playing some role in reducing information asymmetry, which is believed to be one of the main reasons for underinvestment. This is in contrast to the result obtained for overinvestment. Managerial incentives and moral hazard play larger roles in the case of over-investment, and it seems like FRQ is affecting over-investment and under-investment differently.

**Financial constraints and underinvestment in labour**

[5] The correlations between the dependent and independent variables are assessed to ensure that: (1) the dependent and independent variables have the predicted signs in their associations; and (2) multicollinearity is not evident. To substantiate non-multicollinearity results, the data is tested for multicollinearity using the variance inflation factor (VIF) test as well (See Appendix C). it is to be noted that the results reveal a positive relationship between firm size and financial reporting quality (FRQ). This finding is consistent with the theoretical expectation that larger firms face stronger monitoring pressures and reputational incentives, which encourage higher-quality financial reporting (Biddle & Hilary, 2006; Bushman et al., 2011).

We present the effect of financial constraints on the link between FRQ and underinvestment. Following Sualihu et al., 2021; Khedmati et al., 2020; Ben-Nasr and Alshwer, 2016, and Foucault and Frésard, 2012, external financing dependence (EF)[6] has been calculated as the industry-median value of the difference between capital expenditures and cash flow from operations scaled by capital expenditures as a proxy for financial constraints.

External Financing Dependence (EF) =
Industry Median Value of ( $\frac{Capital\ Expenditures - Cash\ Flow\ from\ Operations}{Capital\ Expenditures}$ )

$$|ABN\ (Labour\ Investment)|_{i,t} = \delta_0 + \delta_1 FQ_{i,t-1} + \delta_2 MTB_{i,t-1} + \delta_3 SIZE_{i,t-1} + \delta_4 Quick_{i,t-1} + \delta_5 Lev_{i,t-1} + \delta_6 Divi_{i,t-1} + \delta_7 Std\ CFO_{i,t-1} + \delta_8 Std\ Sales_{i,t-1} + \delta_9 Tangible_{i,t-1} + \delta_{10} EF_{i,t-1} + \delta_{11} EF_{i,t-1} * FQ_{i,t-1} + \delta_{12} Loss_{i,t-1} + \delta_{13} Insti_{i,t-1} + \delta_{14} Std\ Net\ Hire_{i,t-1} + \delta_{15} Labour\ Intensity_{i,t-1} + \delta_{16} Union_{i,t-1} + \delta_{17} |AB\ Invest\ Other|_{i,t} + \varepsilon_{i,t} \quad \ldots (4)$$

A higher value of EF for a specific industry indicates that a firm belonging to this industry has a higher probability of being highly financially constrained.

We are mostly interested in the interaction term $EF_{I,t-1} * FQ_{I,t-1}$, whose coefficient is expected to be negative, suggesting that the negative relationship between underinvestment and FRQ is more pronounced for more financially constrained firms.

Table 4 Panel A shows that the coefficient of the interaction term is negative and significant, indicating that increasing FRQ mitigates underinvestment among financially constrained firms. This finding aligns with the agency and information asymmetry literature, which posits that high-quality reporting reduces uncertainty for external financiers and improves the monitoring of managerial investment decisions (Biddle & Hilary, 2006; Bushman et al., 2011).

Increasing FRQ by one standard deviation is associated with a reduction in underinvestment of 6.07% (against 4.23% when financial constraints are not considered).

Recent empirical have used interest coverage ratio (ICR), size, debt capacity, etc., as measures of financial constraints.

ICR: In line with the work of Altaf and Ahmad, 2019; and Benmelch, 2021, firms have been categorised as financially constrained firm if they have an ICR below the sample median and vice versa. A lower ICR is indicative of greater financial constraint because it signals a firm's reduced capacity to meet its interest payments from operating earnings. Such firms face tighter liquidity positions, limited borrowing capacity, and heightened vulnerability to financial distress. Conversely, firms with higher ICRs possess stronger debt-servicing ability, greater financial flexibility, and improved access to external finance.

Firm size: Size is considered a proxy for financial constraint as large firms will likely enjoy privileged access to external financing and, hence, will be less financially constrained (Baños-Caballero et al. 2014, Faulkender and Wang 2006). Hennessy and Whited (2007) estimated that financing costs are almost twice for small firms as for large firms. Firm size is measured by taking the natural logarithm of total assets. We classify firm observation as 'large'

[6] The external finance (EF) measure from the Rajan and Zingales (1998) framework remains suitable in the Indian context because it reflects industry-specific technological needs rather than country-level financial structures. Prior studies argue that such industry-level dependence indicators are largely stable across countries and retain explanatory power even in emerging markets (Fisman and Love, 2004; Carlin and Mayer, 2003). Empirical work on India similarly employs this measure to analyse sectoral financing patterns (Ayyagari, Demirgüç-Kunt and Maksimovic, 2010; Ghosh, 2010), suggesting that the EF metric can effectively capture cross-industry differences in external financing requirements despite India's bank-dominated financial system and reliance on internal funds & retained earnings.

if the firm's value of assets is above that of the median of the sample firms during that year. Rest are classified as 'small'.

Debt Capacity: Following Almeida and Campello (2007), we consider net tangible worth or debt capacity as a proxy for measuring financial constraint. The rationale is that the high value of tangible assets enable firms to have easier access to external funds. We define debt capacity (Tangible net worth) = Net worth–Intangible net worth. Higher debt capacity implies unconstrained firms.

We test whether our findings with each of these three measures.

Table 4 Panel B shows that the results using three different measures of financial constraint are consistent with the results observed in Table 4 Panel A. Overall, higher FRQ is associated with a reduction in underinvestment in labour in both groups created on the basis of Size and Debt Capacity. However, the coefficient on FRQ for financially unconstrained firms (columns 2 and 3) is smaller than the coefficient for financially constrained firms (columns 1 and 4), indicating that the effect of FRQ on labour investment is more prominent for financially constrained firms. The coefficient of the FRQ (Column 6) is negative and significant for the group with low ICR implying financially constrained. This indicates that increasing FRQ is associated with reduced underinvestment in labour only for financially constrained firms. Increasing FRQ by one standard deviation is associated with a reduction in Underinvestment of 7.13% (6.15%) for firms classified as Size Constrained (Debt capacity constrained) and 5.56% (5.18%) for unconstrained firms. Overall, these results support hypothesis 3, indicating that the relation between FRQ and Underinvestment in labour is stronger for financially constrained firms.

**Overinvestment and large cash balance and free cash flows**

To examine the hypothesis that the relation between financial reporting quality and overinvestment is stronger for firms holding large cash balances and free cash flows, the following two equations are considered:

$$Overinvest_{i,t} = \delta_0 + \delta_1 FQ_{i,\,t-1} + \delta_2 High\ Cash_{i,t-1} + \delta_3 FRQ{*}High\ Cash_{i,t-1} + Control + \varepsilon_{i,t} \quad \ldots\ldots \text{(5a)}$$

$$Overinvest_{i,t} = \delta_0 + \delta_1 FQ_{i,\,t-1} + \delta_2 Free\ Cashflow_{i,t-1} + \delta_3 FRQ{*}Free\ Cashflow_{i,t-1} + Control + \varepsilon_{i,t} \quad \ldots\ldots \text{(5b)}$$

where: *High Cash* is an indicator variable, coded as '1' if the firm is above the median in the distribution of cash balances deflated by total assets in a given year and '0' otherwise. *Free Cash Flow* is equal to cash flow from operations plus R&D expenses minus depreciation and the predicted labour investment for the firm. *Free Cash Flow* is recorded as an indicator variable coded as '1' if the computation of free cash flow is positive and '0' otherwise. The *Control* $_{i,t-1}$ are the control variables used in Eq. (3).

The relationship between financial reporting quality and Overinvestment has been predicted to be stronger for firms with large cash balances and free cash flows because these firms are more likely to overspend existing resources (Jensen, 1986).

In Table 5, the results show that the estimated coefficient on the interaction terms is not statistically significant, which implies that the relation between financial reporting quality and overinvestment is not significantly affected by large cash balances and free cash flows. Our analysis indicates that the relationship between financial reporting quality (FRQ) and overinvestment is not significantly influenced by firms' cash holdings or free cash flow. This suggests that, unlike underinvestment, the presence of internal liquidity does not amplify or mitigate the effect of FRQ on managerial overinvestment. In other words, even firms with large cash reserves or high free cash flows do not significantly alter the link between reporting quality and excessive investment, indicating that FRQ alone is insufficient to curb overinvestment tendencies. These findings are consistent with prior literature suggesting that while high FRQ reduces information asymmetry and enhances monitoring, its effectiveness in constraining overinvestment may be contingent on additional governance mechanisms beyond internal liquidity (Jensen, 1986; Biddle & Hilary, 2006). Thus, the results do not support hypothesis 4 that FRQ reduces overinvestment for firms with large cash balances and free cash flows.

The results show no significant association between FRQ and the positive values of abnormal net hiring. This insignificant effect likely reflects the fact that Indian managers operate in an environment marked by substantial labour adjustment costs—such as high hiring and firing frictions, retraining expenses, and institutional rigidities—that render labour a quasi-fixed input (Oi, 1962; Hamermesh & Pfann, 1996). Empirical evidence shows that India's labour market is among the most regulated globally, with stringent dismissal rules under the Industrial Disputes Act and high separation costs that restrict firms' ability to adjust employment (Besley & Burgess, 2004; Dougherty, 2009; Hasan et al., 2012).Under labour adjustment cost theory, when such frictions are pervasive, managers have limited flexibility to alter workforce levels even in the presence of more transparent and higher-quality financial information. As a result, overinvestment in labour is driven more by structural and regulatory rigidities than by informational factors. Additionally, weak enforcement and monitoring in India's regulatory environment further dilute the disciplining role of financial reporting, reducing managers' reliance on disclosures when making labour expansion decisions (La Porta et al., 1998; Bushman & Piotroski, 2006). Collectively, these features of the Indian labour market help explain why FRQ does not significantly influence overinvestment behaviour as captured by positive abnormal net hiring.

More importantly, we find that FRQ plays a more pivotal role in mitigating labor investment inefficiency due to underinvestment, especially when firms face higher financial constraints. In subsample analyses, although higher FRQ is negatively associated with underinvestment in labor for all firms, the effect is stronger for financially constrained firms. This suggests that although the FRQ plays a role in mitigating underinvestment in labour in financially unconstrained firms, such a relation is even stronger in constrained firms because of a greater need to finance labour. In contrast, we find FRQ does not enhance labor investment efficiency for firms by controlling overinvestment for firms with large cash balances and free cash flows.

Although more work is needed to understand the mechanism, the results of this paper suggest that in the presence of high information asymmetry, FRQ seems to be of greater value to firms who are financially constrained and, therefore, may be choosing sub-optimal investment in the form of under-investment. Small businesses often choose underinvestment due to financial constraints and cannot signal their projects' viability to potential investors. Choosing high-quality FRQ can address this.

## Conclusion

Using a sample of Indian non-financial firms over the period 2007-2019, this study shows that the relation between FRQ and underinvestment in labour is more pronounced for financially constrained firms, consistent with the argument that better FRQ can reduce the information asymmetry between the firm and investors, and thus lower the firm's cost of raising funds. Overall, we find that FRQ is negatively associated with underinvestment in labour. The results presented here are consistent with the view that better FRQ resolves informational asymmetry and, hence, impacts decisions regarding labour investment.

More importantly, we also find that the relation between FRQ and abnormal net hiring is prominent for firms that are small in size, have lower debt capacity and have lower ICR. Presumably, financially constrained firms are disadvantaged in an environment of pronounced information asymmetry. This paper, therefore, extends the prior research related to FRQ by showing that financial reporting quality can reduce information asymmetries that hamper efficient corporate labour investment policies.

**Policy Implications of FRQ on Labour Investment Inefficiency**

1. The negative relationship between financial reporting quality (FRQ) and labour investment inefficiency suggests that higher FRQ helps firms allocate labour resources more efficiently, reducing both under- and overinvestment. Policymakers can encourage practices that enhance FRQ—such as stricter disclosure requirements, audit standards, and corporate governance norms—to improve overall labour productivity and capital-labour allocation.
2. Since FRQ appears to have a stronger mitigating effect on underinvestment for financially constrained firms, policy interventions could focus on supporting these firms. For example:

- Incentivizing transparent reporting through tax or regulatory benefits
- Mandating clear labour-related disclosures in financial statements
These measures can help constrained firms signal their creditworthiness, attract external finance, and make more efficient labour investment decisions.

3. The negative relationship between financial reporting quality (FRQ) and labour investment inefficiency highlights the importance of accurate reporting, especially for financially constrained firms. Auditors should ensure robust labour-related disclosures, while regulators such as SEBI can promote transparency and incentivize high-quality reporting. Investors can use FRQ to monitor managerial efficiency in labour allocation. Together, these measures enhance labour investment efficiency, strengthen governance, and improve overall firm performance.
4. High financial reporting quality (FRQ) is especially valuable in labour-intensive industries, where human capital constitutes a major cost. By improving transparency and reliability of labour-related information, FRQ helps reduce under- and overinvestment, facilitates access to external finance to cover quasi-fixed labour obligations such as hiring, severance, and training costs, strengthens monitoring by investors and regulators, and enhances operational efficiency, enabling managers to make more informed labour investment decisions and adjust workforce efficiently while minimizing adjustment costs.

**Managerial Implication**

By strategically enhancing FRQ through better internal controls, detailed disclosures, governance alignment, and proactive communication, managers can reduce information asymmetry, demonstrate operational discipline, and secure financing for labour investments. High-quality reporting thus becomes a strategic tool to improve workforce efficiency and support growth initiatives.

**Suggestions for Future Research**

1. Depending on firm-level characteristics, like size, and industry characteristics, FRQ and labour investment decisions may be dynamically interrelated or jointly determined through latent variables like quality of corporate governance (board independence, CEO duality etc.) and managerial ability.
2. It is possible that FRQ is related to past levels of abnormal net hiring and other firm and industry-level characteristics.
3. Further, appropriately designed qualitative research involving the various stakeholders can shed more light on the role of FRQ vis-a-vis labour investment decisions.

4. To further corroborate the results, alternative proxies of FRQ and labour investment inefficient can be used in the model.
5. Difference in difference (DiD) test can be conducted to examine pre/post Ind -AS analysis.
6. While high financial reporting quality (FRQ) is expected to reduce underinvestment in labour by lowering information asymmetry and improving monitoring, the reverse may also occur. Firms that underinvest in labour often operate with constrained resources, weaker internal controls, or less skilled personnel, which can compromise the accuracy, timeliness, and overall quality of financial reporting. Additionally, managerial cost-cutting or strategic withholding of information associated with underinvestment may further lower FRQ. This creates a feedback loop where underinvestment leads to poorer reporting, reinforcing labour inefficiency. Recognizing this potential for reverse causality is crucial in empirical analyses, as it underscores the need for appropriate identification strategies, such as instrumental variable approaches.
7. Further, labour investment decisions are sensitive to macro variables such as inflation, GDP growth, unemployment rate etc. which can be included in the analysis to have a more comprehensive picture.

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# Appendix A: Variable Definition

| Variable | Definition |
|---|---|
| | |
| $\Delta WC_{i,t}$ | change in non-cash working capital accruals= the change in non-cash current assets minus the change in current liabilities other than short term debts and taxes payable, scaled by lagged total assets i.e., $\Delta WC_{i,t}$ = ($\Delta$*Current Assets*- $\Delta$Cash)- *($\Delta$Current Liabilities- $\Delta$short-term debts in current liabilities)*. |
| $CFO_{i,t-1}$ | The cash flow that created cash flows in the previous year but the effect of them on earnings took place in the year t. |
| $CFO_{i,t}$ | The cash flow that both create cash flows and affect the earnings in the year t. |
| $CFO_{i,t+1}$ | The cash flows that affect the earnings in the period t, although they will create cash flows in the year t+1. |
| $\Delta$ $REV_{i,t}$ | The change in sales revenues between year t-1 and year t. |
| $PPE_{i,t}$ | Gross value of property, plant and equipment in year t. |
| $\varepsilon_{i,t+1}$ | Represents accruals that are not turned into cash i.e., currents accruals that are unrelated to cash flow realizations and non-discretionary accruals and can't be explained by a change in revenue and the level of PPE. |
| RETURN | Firm's earnings before interest and taxes / Lagged Total assets. |
| Size | The natural log of total assets at the beginning of the year. |
| ROA | The ratio of net income (profit after tax reported by the company) over total assets to control for the firm's current profitability. |
| QUICK | Ratio of the sum of cash and receivables over current liabilities, to control for the firm's current year liquidity. |
| Leverage | Ratio of Total Borrowings for firm i at year t and total assets for firm i at year t. |
| MTB | ratio of market to book value of common |

| | |
|---|---|
| Divi | 1 if the firm pays dividends in the previous year, zero otherwise. |
| Std CFO | The standard deviation of cash flows from operating over years t-3 to t-1 divided by total assets. |
| Std Sales | The standard deviation of sales revenue over years t-3 to t-1 divided by the mean value of past three-year sales. |
| Tangible | The ratio of PPE and total assets at the beginning of the year. |
| Loss | 1 if the firm reported a loss in the previous year, 0 otherwise. |
| Insti | The proportion of outstanding common shares held by institutions at the end of the year t-1. |
| Std Net Hire | The standard deviation of the percentage of employees over years t-3 to t-1. |
| Labor Intensity | Natural log of the ratio of employees and total assets at the beginning of the year. |
| \|AB Invest Other\| | absolute value of residuals from the following regression model based on Biddle, et al., 2009; Jung, et al., 2014, 2016; Ben Nasr, 2016; Lopatta, et al., 2020:<br><br>$\text{Invest Other}_{i,t} = \beta_0 + \beta_1 \text{SalesGrowth}_{i,t-1} + \xi_{i,t}$<br><br>Where $\text{Invest Other}_{i,t}$ = (Capital Exp+ Acquisition Exp+ R&D Exp- Cash Receipts from Sales of PPE)/ Total $\text{Assests}_{t-1}$ |

## Appendix B: List of industries included

| NIC Code Classification 2008 | Name of Industry | Number of firms |
|---|---|---|
| **10** | Manufacture of Food Products | 12 |
| **20** | Manufacturing of Chemicals and Chemical Products | 40 |
| **21** | Manufacture of pharmaceuticals, medicinal chemical and botanical products | 34 |
| **22** | Manufacture of rubber and plastics products | 16 |
| **23** | Manufacture of other non-metallic mineral products | 19 |
| **24** | Manufacture of basic metals | 18 |
| **27** | Manufacture of electrical equipment | 12 |
| **28** | Manufacture of machinery and equipment | 15 |
| **29** | Manufacture of motor vehicles, trailers and semi-trailers | 15 |
| **41** | Construction of buildings | 11 |
| **42** | Civil engineering | 12 |
| **46** | Wholesale trade, except of motor vehicles and motorcycles | 15 |
| **52** | Warehousing and support activities for transportation | 12 |
| **62** | Computer programming, consultancy and related activities | 18 |

## Appendix C: Multicollinearity Test using the variance inflation factor (VIF)

| Variable | VIF | 1/VIF |
|---|---|---|
| **FRQ*EF** | **1.99** | **0.503576** |
| **Size** | **1.91** | **0.524673** |
| **EF** | **1.89** | **0.530009** |
| **Insti** | **1.5** | **0.667444** |
| **FRQ** | **1.32** | **0.760116** |
| **LOSS** | **1.29** | **0.775724** |
| **Leverage** | **1.28** | **0.782652** |
| **LabourIntensity** | **1.25** | **0.79694** |
| **TANGIBLE** | **1.22** | **0.818785** |
| **StdNetHire** | **1.22** | **0.820025** |
| **STDSales** | **1.14** | **0.880336** |
| **Other Invest** | **1.13** | **0.885467** |
| **STDCFO** | **1.09** | **0.914044** |
| **Quickt** | **1.09** | **0.917475** |
| **MTB** | **1.06** | **0.939517** |
| **DIVIDEND** | **1.03** | **0.970146** |

## Table 1: Descriptive Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Abnormal net hiring** | 3237 | .194 | .308 | 0 | 2.376 |
| **FRQ** | 3237 | -.046 | .059 | -.752 | 0 |
| **MTB** | 3237 | 4.312 | 5.241 | -6.493 | 38.935 |
| **Size** | 3237 | 7.528 | 1.596 | 0 | 11.799 |
| **DIVIDEND** | 3237 | .737 | .44 | 0 | 1 |
| **STDCFO** | 3237 | .05 | .046 | -.009 | .317 |
| **STDSales** | 3237 | .247 | .297 | 0 | 1.732 |
| **TANGIBLE** | 3237 | .439 | .263 | 0 | 1.193 |
| **LOSS** | 3237 | .052 | .268 | 0 | 1 |
| **Leverage** | 3237 | .191 | .175 | 0 | .712 |
| **Insti** | 3237 | 18.857 | 14.167 | 0 | 56.42 |
| **StdNetHire** | 3237 | 8.038 | 21.815 | -41.097 | 154.587 |
| **LabourIntensity** | 3237 | .11 | 1.489 | -4.993 | 6.164 |
| **Other Invest** | 3237 | .054 | .057 | -1.534 | .245 |
| | | | | | |
| **underinvest** | 2258 | .139 | .122 | 0 | .879 |
| **overinvest** | 979 | .32 | .507 | 0 | 2.376 |

## Table 2: Pearson Correlations between Variables used in Labour Investment Efficiency Model

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **(1) Abnormal nethiring** | 1.000 | | | | | | | | | | | | | | |
| **(2) FRQ** | 0.010 | 1.000 | | | | | | | | | | | | | |
| **(3) MTB** | 0.035* | -0.020 | 1.000 | | | | | | | | | | | | |
| **(4) Size** | -0.001 | 0.111* | -0.013 | 1.000 | | | | | | | | | | | |
| **(5) DIVIDEND** | -0.022 | -0.003 | -0.014 | 0.055* | 1.000 | | | | | | | | | | |
| **(6) STDCFO** | 0.002 | -0.057* | 0.119* | -0.176* | 0.005 | 1.000 | | | | | | | | | |
| **(7) STDSales** | 0.010 | -0.143* | 0.117* | -0.140* | -0.071* | 0.206* | 1.000 | | | | | | | | |
| **(8) TANGIBLE** | -0.016 | 0.084* | -0.180* | -0.129* | -0.026 | -0.011 | -0.141* | 1.000 | | | | | | | |
| **(9) LOSS** | -0.006 | -0.020 | 0.024 | -0.039* | -0.053* | 0.048* | 0.069* | -0.024 | 1.000 | | | | | | |
| **(10) Quickt** | -0.005 | 0.014 | -0.036* | -0.065* | 0.049* | -0.059* | 0.020 | -0.189* | -0.050* | 1.000 | | | | | |
| **(11) Leverage** | 0.032* | -0.086* | -0.176* | 0.021 | -0.045* | 0.067* | 0.050* | 0.246* | 0.173* | -0.328* | 1.000 | | | | |
| **(12) Insti** | -0.005 | 0.128* | -0.019 | 0.541* | 0.002 | -0.164* | -0.141* | -0.101* | -0.085* | 0.030* | -0.162* | 1.000 | | | |
| **(13) StdNetHire** | 0.005 | 0.042* | 0.023 | 0.351* | -0.060* | -0.072* | -0.049* | -0.035* | 0.025 | 0.013 | -0.031* | 0.217* | 1.000 | | |
| **(14) LabourIntensity** | -0.106* | 0.014 | 0.026 | -0.336* | 0.036* | 0.036* | -0.020 | 0.142* | -0.070* | 0.102* | -0.186* | -0.117* | 0.074* | 1.000 | |
| **(15) Other Invest** | 0.028 | -0.060* | 0.004 | -0.165* | -0.037* | 0.046* | 0.097* | 0.045* | -0.257* | 0.013 | 0.062* | -0.110* | -0.029 | 0.101* | 1.000 |

**** p<0.01, ** p<0.05, * p<0.1*

*This table presents Pearson pairwise correlation coefficients between the regression variables of Eq3*

## Table 3: The Effect of FRQ on Over- and Under-Investment

| VARIABLES | Over-investment in Labour Subsample (Abnormal Net Hiring>0) | Under-investment in Labour Subsample (Abnormal Net Hiring<0) |
|---|---|---|
| **FRQ** | -0.0690 | -0.0997** |
| | (0.296) | (0.0431) |
| **MTB** | -0.0123* | |
| | (0.00703) | (0.000667) |
| **Size** | -0.190*** | 0.00152 |
| | (0.0632) | (0.00535) |
| **DIVIDEND** | 0.162** | -0.00487 |
| | (0.0643) | (0.00778) |
| **STDCFO** | -0.321 | 0.0313 |
| | (0.464) | (0.0612) |
| **STDSales** | 0.0367 | 0.00426 |
| | (0.0541) | (0.00994) |
| **TANGIBLE** | 0.137 | 0.00471 |
| | (0.167) | (0.0183) |
| **LOSS** | -0.152** | 0.0143 |
| | (0.0715) | (0.0157) |
| **Quick** | 0.0451* | -0.000493 |
| | (0.0270) | (0.00259) |
| **Leverage** | 0.0254 | 0.00148 |
| | (0.0179) | (0.00360) |
| **Insti** | 1.20e-05 | 0.000839** |
| | (0.00218) | (0.000325) |
| **StdNetHire** | -0.00372*** | 6.01e-05 |
| | (0.00136) | (0.000170) |
| **LabourIntensity** | -0.320*** | 0.00912** |
| | (0.0536) | (0.00373) |
| **\|AB Invest Other\|** | 0.210 | -0.0518 |
| | (0.307) | (0.0530) |
| **Constant** | 1.575*** | 0.105** |
| | (0.480) | (0.0432) |
| **Firm Fixed Effects** | Yes | Yes |
| **Year Fixed Effects** | Yes | Yes |
| **Observations** | 939 | 2,257 |
| **R-squared** | 0.460 | 0.482 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(Firm fixed effects have been included to control for unobservable industry heterogeneity. Year fixed effects represent year dummies to control for time-specific factors in a firm's hiring. Standard errors by firm and year have been clustered to control for cross-sectional and intertemporal correlation.

**Table 4: Role of Financial Constraints**
**Panel A: Relation between FRQ and underinvestment in the presence of Financial Constraint**

| VARIABLES | Under investment |
|---|---|
| **FRQ** | -0.143*** |
| | (0.0499) |
| **MTB** | 5.73e-05 |
| | (0.000665) |
| **Size** | 0.00155 |
| | (0.00537) |
| **DIVIDEND** | -0.00543 |
| | (0.00777) |
| **STDCFO** | 0.0315 |
| | (0.0610) |
| **STDSales** | 0.00423 |
| | (0.00992) |
| **TANGIBLE** | 0.00453 |
| | (0.0184) |
| **LOSS** | 0.0153 |
| | (0.0156) |
| **Quick** | -0.000600 |
| | (0.00258) |
| **Leverage** | 0.00163 |
| | (0.00357) |
| **Insti** | 0.000823** |
| | (0.000325) |
| **StdNetHire** | 5.18e-05 |
| | (0.000169) |
| **LabourIntensity** | 0.00917** |
| | (0.00373) |
| **\|AB Invest Other\|** | -0.0549 |
| | (0.0530) |
| **EF** | -0.00203 |
| | (0.00261) |
| **FRQ*EF** | -0.0735* |
| | (0.0380) |
| **Constant** | 0.105** |
| | (0.0434) |
| **Firm Fixed Effects** | Yes |
| **Year Fixed Effects** | Yes |
| **Observations** | 2,257 |
| **R-squared** | 0.483 |

**Note:** EF is a proxy for financial constraint implying external finance dependence.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(Firm fixed effects have been included to control for unobservable industry heterogeneity. Year fixed effects represent year dummies to control for time-specific factors in a firm's hiring. Standard errors by firm and year have been clustered to control for cross-sectional and intertemporal correlation.

**Table 4, Panel B: The role of financial constraints (different proxies) for underinvested firms**

| | Size | | Debt capacity | | ICR | |
|---|---|---|---|---|---|---|
| **VARIABLES** | **Large** | **Small** | **Higher** | **Lower** | **High** | **Low** |
| **FRQ** | -0.131** | -0.168** | -0.122** | -0.145* | -0.0748 | -0.127* |
| | (0.0569) | (0.0844) | (0.0474) | (0.0871) | (0.0626) | (0.0649) |
| **MTB** | 0.00155 | -0.00146 | 0.00133 | -0.00347*** | 0.000902 | -0.00113 |
| | (0.00101) | (0.00111) | (0.000994) | (0.00111) | (0.00111) | (0.000811) |
| **Size** | 0.00548 | 0.0273 | 0.00704 | 0.00332 | 0.00739 | -0.0195* |
| | (0.00783) | (0.0183) | (0.00781) | (0.0176) | (0.00791) | (0.0104) |
| **DIVIDEND** | 0.000955 | -0.00213 | -0.00973 | -0.000521 | 0.000676 | 1.25e-05 |
| | (0.0132) | (0.0107) | (0.0131) | (0.0110) | (0.0102) | (0.0126) |
| **STDCFO** | -0.0298 | 0.264** | -0.0120 | 0.264** | 0.0594 | 0.0683 |
| | (0.0834) | (0.106) | (0.0839) | (0.114) | (0.0875) | (0.0939) |
| **STDSales** | 0.00304 | -0.00159 | -0.000825 | 0.00586 | 0.0102 | -0.00705 |
| | (0.0109) | (0.0217) | (0.0108) | (0.0228) | (0.0144) | (0.0158) |
| **TANGIBLE** | -0.0152 | 0.0292 | 0.00159 | 0.0494* | 0.00878 | -0.0244 |
| | (0.0304) | (0.0246) | (0.0324) | (0.0263) | (0.0314) | (0.0227) |
| **LOSS** | 0.0140 | 0.00271 | 0.00813 | -0.00705 | 0.00941 | 0.0405 |
| | (0.0186) | (0.0259) | (0.0189) | (0.0299) | (0.0175) | (0.0454) |
| **Quick** | -0.00248 | 0.00198 | -0.00224 | -0.000880 | -0.00360 | 0.00389 |
| | (0.00411) | (0.00418) | (0.00434) | (0.00404) | (0.00413) | (0.00338) |
| **Leverage** | -0.00330 | 0.0126 | -0.00457 | 0.0222* | 0.00368 | 0.000854 |
| | (0.00559) | (0.00878) | (0.00460) | (0.0131) | (0.00451) | (0.00762) |
| **Insti** | 0.000421 | 0.000594 | 0.000557 | 0.000515 | 0.000852* | 0.00106* |
| | (0.000475) | (0.000610) | (0.000494) | (0.000579) | (0.000486) | (0.000545) |
| **StdNetHire** | 0.00160 | -0.000137 | -0.00149 | 1.19e-05 | -0.000140 | 0.000210 |
| | (0.00184) | (0.000192) | (0.000964) | (0.000197) | (0.000272) | (0.000241) |
| **LabourIntensity** | 0.0106** | 0.0355*** | 0.0120** | 0.0244** | 0.0182*** | 0.00704 |
| | (0.00524) | (0.0108) | (0.00510) | (0.00952) | (0.00659) | (0.00562) |
| **\|AB Invest Other\|** | -0.0128 | -0.0516 | -0.0248 | -0.00981 | -0.0178 | 0.0403 |
| | (0.0757) | (0.0816) | (0.0781) | (0.0808) | (0.0796) | (0.0720) |
| **Constant** | 0.0794 | -0.129 | 0.0765 | 0.0811 | 0.0524 | 0.264*** |
| | (0.0583) | (0.157) | (0.0601) | (0.150) | (0.0646) | (0.0820) |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Firm Fixed Effects** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year Fixed Effects** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Observations** | 1,110 | 1,103 | 1,125 | 1,092 | 1,120 | 1,077 |
| **R-squared** | 0.469 | 0.569 | 0.477 | 0.558 | 0.536 | 0.557 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(Firm fixed effects have been included to control for unobservable industry heterogeneity. Year fixed effects represent year dummies to control for time-specific factors in a firm's hiring. Standard errors by firm and year have been clustered to control for cross-sectional and intertemporal correlation.

**Table 5: Relation between FRQ and overinvestment for firms with large cash balance and free cash flows.**

| VARIABLES | (1) Overinvest | (2) Overinvest |
|---|---|---|
| **FRQ** | -0.191 | -0.372 |
| | (0.340) | (0.422) |
| **MTB** | -0.0125* | -0.0125* |
| | (0.00702) | (0.00702) |
| **Size** | -0.192*** | -0.186*** |
| | (0.0637) | (0.0628) |
| **DIVIDEND** | 0.162** | 0.163** |
| | (0.0642) | (0.0642) |
| **STDCFO** | -0.330 | -0.316 |
| | (0.465) | (0.460) |
| **STDSales** | 0.0392 | 0.0401 |
| | (0.0536) | (0.0551) |
| **TANGIBLE** | 0.129 | 0.139 |
| | (0.168) | (0.166) |
| **LOSS** | -0.152** | -0.146** |
| | (0.0718) | (0.0713) |
| **Quick** | 0.0454* | 0.0447* |
| | (0.0271) | (0.0271) |
| **Leverage** | 0.0249 | 0.0250 |
| | (0.0179) | (0.0180) |
| **Insti** | 3.34e-05 | 0.000136 |
| | (0.00218) | (0.00218) |
| **StdNetHire** | -0.00372*** | -0.00383*** |
| | (0.00136) | (0.00137) |
| **Labour Intensity** | -0.318*** | -0.318*** |
| | (0.0536) | (0.0535) |
| **\|AB Invest Other\|** | 0.216 | 0.218 |
| | (0.309) | (0.308) |
| **Cash dummy** | 0.0350 | |
| | (0.0454) | |
| **FRQ*cash dummy** | 0.327 | |
| | (0.507) | |
| **Free cash flow dummy** | | 0.00292 |
| | | (0.0576) |
| **FRQ*Free cash flow dummy** | | 0.666 |
| | | (0.526) |
| **Constant** | 1.578*** | 1.545*** |
| | (0.481) | (0.481) |
| **Firm Fixed Effects** | Yes | Yes |
| **Year Fixed Effects** | Yes | Yes |
| **Observations** | 939 | 939 |
| **R-squared** | 0.461 | 0.462 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(Firm fixed effects have been included to control for unobservable industry heterogeneity. Year fixed effects represent year dummies to control for time-specific factors in a firm's hiring. Standard errors by firm and year have been clustered to control for cross-sectional and intertemporal correlation.

# Digital Financial Services: An Empirical Analysis

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## Abstract

The present study aims to assess the impact of financial literacy (FL) and digital literacy (DL) on the intention towards utilizing digital financial services (IUDFS), as well as the effect of intention on actual usage (AU). A total of 391 valid and insightful responses have been obtained from adults in Haryana who use digital financial services (DFS) through primary quantitative research, and these responses have been analysed utilizing SPSS 26 and Smart PLS 4 software. The results underscore the importance of FL and DL as pivotal determinants influencing IUDFS. Further, it is revealed by the study that IUDFS has a positive impact on AU. The insights derived from this study are of significant value as they equip marketers with a more profound comprehension of their customers by integrating the most recent insights on digital literacy and financial literacy, thereby facilitating informed decision-making and strategic formulation for financial inclusion. Policymakers can leverage insights from this study to formulate policies that promote both financial and digital literacy, recognizing them as essential elements for enhancing digital financial inclusion.

**Keywords:** Financial Literacy, Financial Services, Inclusion, Digital Literacy, Intention

## Introduction

Digital technology has made major strides in financial inclusion in recent years, especially through the digitization of the financial system and new business models. In a rapidly digitizing country like India, Digital Financial Services (DFS) offer a promising solution to extend financial access to underserved, remote, and marginalized communities (Buteau et al., 2021). DFS enhances accessibility, streamlines processes, and enables real-time economic assessments. However, a critical barrier remains: limited digital and financial competencies among users (Li et al., 2023), especially small business owners who require these skills to fully leverage DFS platforms (Uthaileang & Kiattisin, 2023).

As digital tools like wallets, robo-advisors, crypto currencies, and peer-to-peer lending become increasingly complex, there is a greater need for strong digital and financial literacy (Isaia & Oggero, 2022).. Digital financial inclusion aims to provide affordable, formal financial services to excluded populations by leveraging modern technologies like the Internet, big data, and cloud computing (Ozili, 2018; 2021). This digital shift emphasizes risk management, efficient information flow, and equitable access to user-friendly financial services (Das, 2019).

Strong digital and financial literacy is crucial for fostering a sustainable digital banking ecosystem (Suparno et al., 2023; Bojuwon et al., 2023). Financial literacy goes beyond knowledge; it involves the ability to make informed decisions that impact individual financial well-being (Lusardi & Mitchell, 2014; Hasan & Hoque, 2021). A lack of financial knowledge can exclude individuals from DFS, limiting their economic empowerment (Yang, Wu & Huang, 2023).

Digital literacy refined as the ability to effectively use of digital tools for communication, learning, and productivity is equally vital (Becirovic et al., 2023). It enables users to access crucial services related to jobs, healthcare, education, and entrepreneurship, particularly in developing countries (Ali, Raza & Qazi, 2023; Wang & Huang, 2022). Despite its importance, digital literacy in India remains uneven, with only 25% of rural households considered digitally literate, compared to 61% in urban areas (Agarwal, 2023).

Previous studies affirm the role of DFS in enhancing financial inclusion by improving access to credit, encouraging savings, and increasing financial service usage (Demirgüç Kunt et al., 2018; Ouma et al., 2017). Yet, the success of DFS is closely tied to users' literacy levels. While financial inclusion has been studied through indicators such as account ownership and affordability (Iqbal & Sami, 2017), limited research explores the combined impact of digital and financial literacy in enabling effective DFS usage.

## Research Gap

Various published reports and articles, such as those by (Prasad et al., 2018; Liew et al., 2020; Azeez & Akhtar, 2021) have recognized the significance of skills and literacy. Previous research typically focused solely on evaluating the impact of financial literacy (FL) on the DFS adoption and use, rather than considering the interplay between FL and DL within the digital finance sphere (Li et al., 2020; Yoshino et al., 2020; Kass-Hanna et al., 2022). The components of behavioral intentions have been the subject of different studies in the past, as shown by the studies by Weismueller et al., (2020), Prentice et al., (2019), and Jung et al., (2021). Furthermore, scholars have investigated the relationship between behavioral intentions using TAM, as seen in the work of Hidayatullah et al., (2021) and Jung et al. (2021). Conversely, certain researchers have directed their attention towards digital literacy (DL), as proved by studies conducted by Jamila et al. (2020), Bastomi, Hermawan, and Handayati (2023) and Semente & Whyte (2020). The present study fills a research gap by concentrating on the behavioral intentions of adults who possess both financial and digital literacy. Nevertheless, none of above studies has examined collectively the interplay between FL, DL, and their influence on IUDFS. The present study also seeks to address how intentions to use DFS influence actual usage of DFS as use intention towards DFS serves as a pivotal precursor to digital financial inclusion (Pazarbasioglu et al., 2020). Individuals expressing a strong desire to utilize these services are more likely to actively interact with and adopt digital financial tools and platforms. This intention acts as a driving force, prompting individuals to explore and incorporate digital financial services into their financial practices. As users actively participate in digital financial services, they contribute to the growth and accessibility of digital financial inclusion. Their engagement enhances the overall usage and adoption rates, fostering a broader reach of digital financial services within diverse segments of the population. Moreover, the intention to use digital financial services often reflects a positive attitude toward technology-driven financial solutions. This positive perception can create a ripple effect, to embrace digital financial tools, and thus contributing to increased digital financial inclusion (Thathsarani & Jianguo, 2022).

## Literature Review and Hypotheses Development

### Financial literacy (FL)

Financial literacy plays a pivotal role in shaping individuals' behavior and decisions concerning various aspects of finance. Studies by Yoshino et al. (2020) have highlighted its positive impact on the utilization of mobile payment apps and crypto currencies. This understanding allows individuals to evaluate risks and make well-informed financial decisions, ensuring that their intentions correspond with their actual behaviors (Ha, Şensoy & Phung, 2023). Moreover, financial literacy encompasses a broad range of economic and financial knowledge crucial for managing resources effectively (Atkinson and Messy, 2011). Badshah et al. (2014) note its short-term influence on investment intentions. However, Albaity & Rahman (2019) found a contradictory correlation between FL and the intention in the realm of Islamic banking services, highlighting the complexity of these interactions. Research also emphasizes the positive correlation between FL and investment intentions (Sadiq & Khan, 2018; Van et al., 2012). Nugroho & Apriliana (2022) demonstrate the significant impact of Islamic financial literacy on the intention to use Go-Pay, indicating the relevance of financial literacy in modern digital finance. Recent studies show that having greater financial literacy correlate with a better grasp of digital financial systems' benefits and functionalities (Yang et al., 2023), fostering an intention to use them effectively (Lusardi & Mitchell, 2011). Therefore, it is expected that the intention to use digital financial instruments and services as their actual use will increase with increasing FL. Based on previous research, the following hypothesis have been developed:
H1. FL is positively attached with IUDFS.
H2. FL exerts a significant and positive effect on Actual Usage (AU).

### Digital literacy (DL)

Numerous prior studies have explored consumers' behavioral inclinations in diverse settings. DL is imperative for acquiring knowledge of novel technologies and adapting to them (Ullah et al., 2022). Studies carried out by Khoiriyah et al. (2022), Jerni et al. (2021) have illustrated that DL distinctly impacts entrepreneurial intentions. Conversely, Palumian et al. (2023) discovered a negative correlation between the inclination to adopt mobile technology and DL. Mulyono (2023) unveiled that the influence of DL on the utilization of fintech services, mediated by FL, is both constructive and noteworthy. Recent research by Bastomi, Hermawan, and Handayati (2023) emphasized the crucial role of DL in molding the predisposition towards digitally-driven entrepreneurship. Suryani & Chaniago (2023) showcased a favorable and remarkable effect of DL on vocational students' entrepreneurial intentions. A study by Jamila et al. (2020) suggested a documented positive link between the acceptance of emerging technologies and individuals' perspectives on digital literacy. In consideration of the aforementioned discourse, the present study concentrates on scrutinizing the association among DL, behavioral intention, and actual usage (AU). As a result, the subsequent hypothesis is formulated.
H3. DL is positively associated with the IUDFS.
H4. DL exerts a significant and positive effect on Actual Usage.

### Behavioral Intention

The Theory of Reasoned Action (TRA), foundational to the Technology Acceptance Model (TAM), posits that behavioral intentions strongly forecast human behaviors. This theory, originating from Ajzen and Fishbein in 1980, asserts that an individual's intention to perform a

specific task directly predicts their actual behavior. Within the domain of behavior, intention and usage are two separate but interconnected elements. These intentions are shaped by motivational factors, signifying the effort and resolve individuals plan to invest, as suggested by Ajzen in 1991. Singh and Sinha (2020) have observed that intention functions as a proximate factor that promotes usage. According to Singh and Sinha (2020), usage, on the other hand, refers to the concrete actions taken after a series of evaluations regarding a particular phenomenon in the adoption of technology. In the context of e-learning, Almaiah and Alyoussef (2019) confirmed the positive influence of intention on actual usage. This intention, crucial for digital financial services' adoption is aligned with earlier studies indicating a positive link between intention and actual adoption (Venkatesh et al., 2012), thereby enhancing financial inclusion (Fitriani & Santi, 2023) by driving adoption and aligning with broader financial inclusion goals (Ullah et al., 2022). Behavioural Intention reflects individuals' attitudes, beliefs, and motivations regarding digital platforms' benefits for financial services, and it influences the actual use. Consequently, the present study proposes the following hypothesis to examine:
H3. Behavioural intention towards DFS influences Actual Usage.

## Conceptual Framework

After reviewing the relevant studies and development of hypotheses, the current study proposed a conceptual framework. The framework consists of variables such as Financial Literacy (FI), Digital Literacy (DI), Intention towards DFS (IUDFS) and Actual Usage (AU). In Figure 1, the study's conceptual framework is presented; highlighting that IUDFS is influenced by FL and DL. Further, AU is influenced by IUDFS.

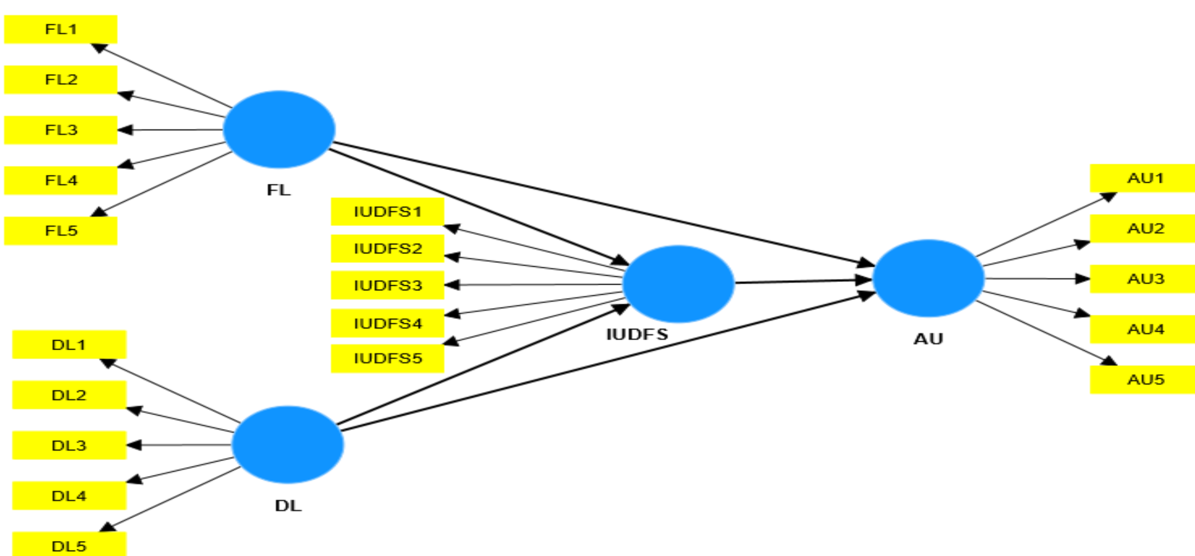


**Figure 1: Conceptual Framework**

## Research Methodology

The current research adopts a descriptive approach. Data collection as well as data analysis is the two main procedural components of the research method of study. For data collection, a well-structured questionnaire was prepared and distributed among adults in Haryana who actively use digital financial services (DFS). The questionnaire was sent to 425 adults on random basis, out of which 412 respondents completed it. After reviewing the completeness of the information provided, 391 questionnaires were found to have all the necessary details. Subsequently, 391 valid responses were included for analysis. A five-point Likert scale was employed to assess the main constructs, with responses ranging from "strongly disagree" (1) to "strongly agree" (5). Structural Equation Modeling (SEM) is widely acknowledged as a powerful technique for evaluating models involving multiple variables. It allows researchers to assess the relationships among variables and evaluate how well the proposed model aligns with the collected data by utilizing various fit indices (Hair et al., 2016). Therefore, this study employed Structural Equation Modeling (SEM) using the Smart-PLS method for statistical analysis. Following the methodology outlined by Hair et al. (2016), the data analysis comprised two main assessments of the model: the external (measurement) model and the internal (structural) model evaluations.

## Data Analysis and Findings

### Analysis of the External Measurement Model

In order to determine whether the external model satisfies the theoretical and retrieval principles, a latent construction test of reflective and formative indicators is used to test it. To put it simply, it evaluates the reliability and validity of the data. Using SmartPLS Version 4's PLS Algorithm, the following four external model evaluations were produced. R2 and Path Coefficient values would be generated concurrently by this process for the purpose of assessing the inner model (Purwanto & Sudargini, 2021). The degree to which the new scale is correlated with other variables and measures of the same construct is evaluated by convergent validity. In addition to showing minimal correlation with dissimilar, unrelated variables, the construct should also show low correlation with related variables. Establishing discriminant validity involves demonstrating that measures of constructs that shouldn't be highly correlated are indeed not highly correlated with each other (Nazzal et al. 2021).

Three fundamental criteria have been used to assess convergent validity in this study: "average variance extracted (AVE)", "composite reliability" and "Cronbach's alpha" for internal consistency, and indicator reliability (factor loading). The acceptable threshold values for evaluating each of the indexes used in this study are shown in Table 1. First, factor loading for the items is also displayed in the table. The fact that all of the items showed acceptable factor loadings (above 0.5) confirmed the reliability of the instruments used to measure each variable. As an additional criterion for assessing convergent validity, Average Variance Extracted (AVE) was used. Convergent validity for all latent variables appears to be sufficient, as shown by Table 1, where the Ave values for all construct range from 0.700 to 0.772, exceeding the required threshold (i.e., >0.5). Measurement of the same phenomenon across all items is known as internal consistency reliability. Two primary criteria are used to measure it: composite reliability and Cronbach's alpha, which has a value from 0 to 1. The values for each construct's Cronbach's alpha and composite reliability (CR) are displayed in Table 1. CR values span from 0.899 to 0.939, whereas range of Cronbach's alpha values is 0.892 to 0.927. It is evident from Table 1 that the threshold values taken into consideration for this study have reached the recommended value for both criteria. As a result, the constructs' internal consistency reliability is established.

**Table 1: Assessment of measurement model**

| Latent Variable | Observed Variable | Factor loading | AVE | Composite Reliability(rho_a) | Cronbach's Alpha | Discriminant Validitity |
|---|---|---|---|---|---|---|
| FL | FL1<br>FL2<br>FL3<br>FL4<br>FL5 | 0.895<br>0.849<br>0.905<br>0.851<br>0.892 | 0.772 | 0.939 | 0.927 | Yes |
| DL | DL1<br>DL2<br>DL3<br>DL4<br>DL5 | 0.836<br>0.857<br>0.831<br>0.827<br>0.897 | 0.722 | 0.91 | 0.904 | Yes |
| IUDFS | IUDFS1<br>IUDFS2<br>IUDFS3<br>IUDFS4<br>IUDFS5 | 0.848<br>0.873<br>0.873<br>0.854<br>0.896 | 0.755 | 0.921 | 0.919 | Yes |
| AU | AU1<br>AU2<br>AU3<br>AU4<br>AU5 | 0.79<br>0.881<br>0.773<br>0.828<br>0.903 | 0.700 | 0.899 | 0.892 | Yes |

Source: Self Developed

**Discriminant Validity**

The Fornell Larcker criterion in table 2 and the Heterotrait Monotrait ratio of correlations (HTMT) in table 3 are the two methods used to assess the measurement model's discriminant validity using the PLS-SEM method. The application of the Fornell & Larcker criterion (table 2) is evident, where the square root values of the AVE for each construct surpass their respective correlation values with another constructs. According to Henseler et al. (2016), this observation is consistent with the standards established by Fornell and Larcker (1981), which reinforcing the assurance of discriminant validity in the study. Table 3 displays the model's HTMT index results. According to the standards established by Henseler et al. (2015), discriminant validity between two reflective constructs is verified when HTMT value is less than 0.90. This is demonstrated by the evaluation of discriminant validity using the Heterotrait-Monotrait ratio of correlations (HTMT). Examining Table 3 reveals that the HTMT values consistently fall below the 0.9 threshold for all constructs. Thus, all of the study's constructs have successfully demonstrated discriminant validity.

**Table 2: Result of Fornell – Larcker Criterion**

| | AU | DL | FL | IUDFS |
|---|---|---|---|---|
| AU | 0.836 | | | |
| DL | 0.478 | 0.85 | | |
| FL | 0.236 | 0.113 | 0.879 | |
| IUDFS | 0.567 | 0.537 | 0.208 | 0.869 |

Source: Self Developed

**Table 3: Results of HTMT indicators**

| | AU | DL | FL | IUDFS |
|---|---|---|---|---|
| AU | | | | |
| DL | 0.525 | | | |
| FL | 0.252 | 0.12 | | |
| IUDFS | 0.624 | 0.585 | 0.221 | |

Source: Self Developed

**Collinearity Phenomenon Testing**

Table 4 displays the collinearity test results. Since there are two dependent variables in the structural model, the VIF coefficient was calculated in the model that includes IUDFS and AU as the dependent variables and the independent variables FL and DL. Table 4's findings show that there is no multicollinearity in the model since all independent variable VIF coefficients are less than 5.

**Table 4: Collinearity Statistics (VIF)**

| | |
|---|---|
| DL -> AU | 1.405 |
| DL -> IUDFS | 1.013 |
| FL -> AU | 1.045 |
| FL -> IUDFS | 1.013 |
| IUDFS -> AU | 1.45 |

Source: Self Developed

**Internal (Structural) Model**

The internal model clarifies the relationships between the variables that are being studied, providing insight into the interactions between independent and dependent factors. Additionally, it measures the what extent to which each independent factor impact the dependent factor. The results of structural models aid in clarifying research questions and the importance of relationships, both favourable and unfavourable. As per the PLS-SEM methodology, the Coefficient of Determination ($R^2$ Value), Predictive Accuracy ($Q^2$), F-square ($F^2$ Value), Hypothesis Testing (e.g., path coefficient) (Hair, 2010), and Model Fit Value (SRMR) are critical benchmarks for evaluating the reliability as well as the precision of the structural model.

**$R^2$ and $Q^2$ of Dependent Constructs**

According to Hair (2010), the R2 value evaluates how much of the endogenous construct's variability is attributable to each of the related exogenous constructs. Table 5 displays the R2 & Q2 values for dependent constructs in this study. The R2 value for actual Usage (AU) is 0.378, indicating a moderate level. Additionally, the value of 0.31 signifies that 31% of the intention towards using digital financial services (IUDFS) is accounted for by financial literacy (FL) and digital literacy (DL). The Q square values for actual usage (AU) and intention toward digital financial services (IUDFS) are 0.301 and 0.252, respectively. The fact that the Q-square value is greater than zero establishes the predictive relevance of the internal model. Further, table 5 also presents the composite model assessed using the "Standardized Root Mean Square Residual (SRMR)" criterion to make sure there is no misspecification. The difference between the observed (sample-derived) and predicted (model-predicted) correlation matrix is assessed by the SRMR. The model demonstrates a good fit to data, given that the SRMR value of 0.04 is under the specified limit of 0.08, as highlighted by Henseler et al. (2016).

**Table 5: R2 Value, Q2 Value & SRMR Value**

| | R-square | R-square adjusted | Q- square | SRMR of saturated Model |
|---|---|---|---|---|
| AU | 0.378 | 0.373 | 0.252 | |
| IUDFS | 0.31 | 0.307 | 0.301 | 0.048 |

Source: Self Developed

**Effect Size ($F^2$) and Model fit Evaluation**

Table 6 exhibits the F-square values derived from the bootstrapping technique, illustrating the degree of influence of latent variables on the dependent variables. As per the recommendations of Suparno et al. (2023) and Hair et al. (2012), the guidelines for measuring $F^2$ effect sizes suggest that values of 0.15, 0.02, and 0.35 represent medium, small, and large impact; respectively. In the case of IUDFS towards AU, $F^2$ value of 0.187 represents a medium to large impact. The digital literacy (DL) factor showcases a $F^2$ value of 0.387 towards IUDFS, suggesting a substantial effect size in comparison to financial literacy (FL), which has a F2 value of 0.032 denoting a small effect (Cohen, 1988). Conversely, the FL and DL variables demonstrate F2 values of 0.023 and 0.068 for AU respectively, indicating a small effect (Cohen, 1988). These evaluations of effect size offer valuable insights into the limit of influence exerted by each latent variable on the dependent variables.

**Table 6: F2 Value**

| | |
|---|---|
| DL -> AU | 0.068 |
| DL -> IUDFS | 0.387 |
| FL -> AU | 0.023 |
| FL -> IUDFS | 0.032 |
| IUDFS -> AU | 0.187 |

Source: Self Developed

**Outcomes of Path Coefficients Direct Relation**

Analyzing the β-value, or path coefficient, is necessary to test hypotheses and examine the importance of the impact among variables (Hair, 2010). The present study employed an operating bootstrapping PLS algorithm test to evaluate these between the independent and dependent variables (Hair et al., 2013). It is critical to evaluate the p-value for every variable when examining relationships. Significant relationships are shown by a p-value $< 0.05$. Table 7 makes it clear that every factor exhibits statistical significance, including FL, DL, IUDFS, and AU. According to the results of the model test, FL and DL have a positive impact on AU and IUDFS. Further, IUDFS has a direct positive impact on AU. For these factors, the corresponding path coefficients are 0.41, 0.52, 0.123, 0.244, and 0.15. Therefore support H1, H2, H3, H4 and H5. The rationale behind these findings will be further elucidated in the subsequent discussion. Figure 2 illustrates the outcomes of the model analysis conducted using the Smart PLS software.

**Table 7: Results for p-values, T Statistics, and Std. Deviation of each factor**

| | Original sample (O) | Sample mean (M) | (STDEV) | T statistics (\|O/STDEV\|) | P values | Result |
|---|---|---|---|---|---|---|
| DL -> AU | 0.244 | 0.245 | 0.051 | 4.773 | 0.000 | Supported |
| DL -> IUDFS | 0.52 | 0.521 | 0.042 | 12.43 | 0.000 | Supported |
| FL -> AU | 0.123 | 0.125 | 0.039 | 3.138 | 0.001 | Supported |
| FL -> IUDFS | 0.15 | 0.151 | 0.044 | 3.379 | 0.000 | Supported |
| IUDFS -> AU | 0.41 | 0.409 | 0.053 | 7.814 | 0.000 | Supported |

Source: Self Developed

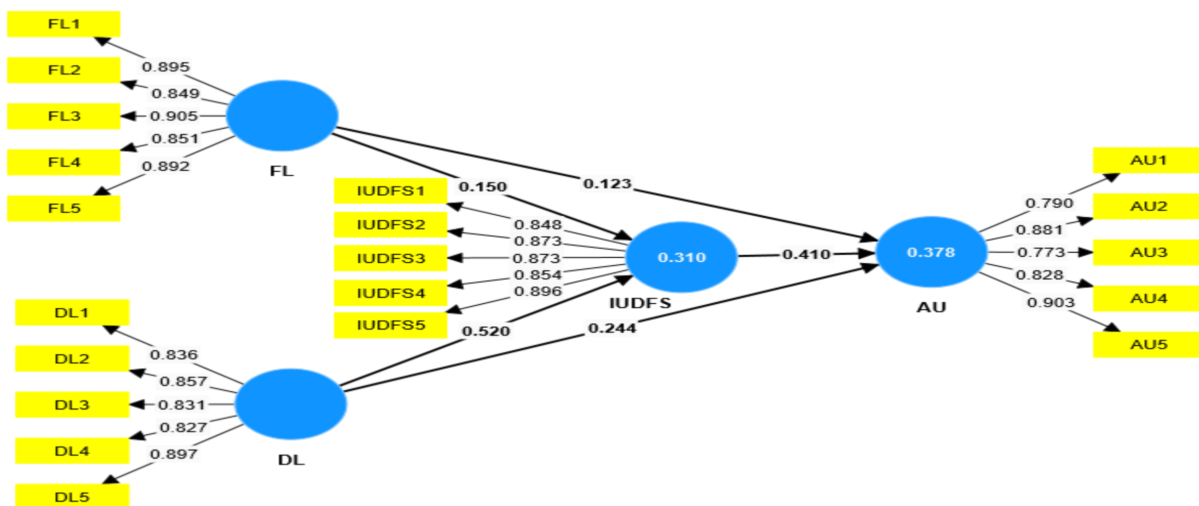


**Figure 2: Model Result**

Source: developed by authors using Smart-PLS

**Common Method Variance**

According to Podsakoff et al. (2003) and Richardson et al. (2009), Common method variance refers to systematic error introduced when a single method is used to measure multiple constructs within a study. If this variance influences the relationships among the measured variables, it can lead to biased or misleading results in the analysis. it indicates the presence of common method bias (Jakobsen & Jensen, 2015; Richardson et al., 2009). To mitigate potential common method bias, researchers often employ Harman's common factor test (Podsakoff & Organ, 1986; Jordan & Troth, 2020). This involves consolidating the proposed variables into a single un-rotated factor to assess if a dominant factor explains more than 50% of the variance. In this study, Harman's single factor score revealed that only 31.32% of the variance was explained by the first component, indicating that common method bias is not a significant concern.

## Discussion

This study has tested the proposed hypotheses using a structural equation model, which indicated a good model fit, evidenced by an SRMR value of 0.050 significantly below the recommended threshold of 0.08 (Henseler et al., 2016). Path coefficients have been interpreted as standardized regression coefficients (Jakobowicz, 2006), enabling clear comparison of effect sizes among variables.

The first two hypotheses examined the impact of financial literacy (FL) on both intention to use digital financial services (DFS) and actual usage. The results provide strong support for H1 ($\beta = 0.15$, $t = 3.379$, $p < 0.001$) and H2 ($\beta = 0.123$, $t = 3.138$, $p = 0.001$), confirming that financial literacy significantly influences both users' intentions and their actual usage with digital financial services. These findings align with previous research (Sadiq & Khan, 2018; Van et al., 2012; Morgan & Trinh, 2020; Yoshino et al., 2020) that highlighted the pivotal role of financial literacy in shaping behavioral intentions and usage patterns. This reinforces the necessity for educational programs and awareness campaigns aimed at improving financial literacy; as such initiatives can empower individuals to make informed decisions and ultimately contribute to enhanced financial inclusion.

Hypothesis H3 has focused on digital literacy (DL) and its effects on intention and actual usage of DFS. The data strongly supports this hypothesis, with a notably high path coefficient for digital literacy's effect on intention ($\beta = 0.498$, $t = 11.321$, $p < 0.001$). This is matched with earlier results by Khoiriyah et al. (2022) and Jerni et al. (2021) regarding the importance of digital literacy (DL) in fostering positive behavioral intentions. Digital literacy facilitates users' comfort with technology, enhances security awareness, improves efficiency in service usage, and encourages continuous learning, all of which contribute to stronger intentions to adopt digital financial services. Furthermore, the positive relationship between digital literacy and actual usage which is consistent with the finding of Mulyono (2023), suggests that higher digital competence translates into more active usage with digital financial platforms. This underscores the critical need to enhance digital literacy as a pathway to broader adoption of digital financial literacy.

Finally, the relationship between intention to use digital financial services (IUTDS) and actual usage (AU) was confirmed ($\beta = 0.41$, $t = 7.814$, $p < 0.001$), supporting hypothesis H4. This results is matched with Almaiah & Alyoussef's (2019) research on e-learning adoption, indicating that a strong behavioral intention is a reliable predictor of actual usage. This highlights the importance of strategies aimed at nurturing positive user intentions to maximize digital financial services uptake, which can facilitate greater financial inclusion and expand access to essential financial services.

## Conclusion

This study investigates the interplay between financial literacy, digital literacy, and their impact on the intention to use digital financial services. It also examines how this intention translates into the actual usage of digital financial services among adults in Haryana. While prior research has explored these literacies separately, studies addressing their combined effect remain limited. To bridge this gap, the study has incorporated four key constructs: digital literacy (DL), financial literacy (FL), intention to use digital financial services, and actual usage. A total of 391 valid responses have been collected through primary quantitative research and analyzed using SPSS 26 and SmartPLS 4. The findings have highlighted that both financial and digital literacy are significant predictors of the intention to use digital financial services. Moreover, the results have revealed that a stronger intention to use these services positively influences actual usage among respondents.

**Implications**

The theoretical implications of this study are twofold. First, it extends existing models by demonstrating how digital and financial literacy jointly influence digital financial behavior, suggesting the need to integrate these competencies into frameworks such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). Second, it highlights evolving nature of financial literacy in a digital context, where traditional notions of knowledge necessarily expanded to include technological aptitude. This combined literacy perspective offers a more nuanced understanding of consumer behaviour in digital financial atmosphere, offering a valuable avenue for future research.

From a practical standpoint, the study suggests that increasing DFS adoption requires more than general awareness; it necessitates targeted, skill-oriented interventions. Educational campaigns should focus on practical training, particularly in rural and semi-urban regions where literacy gaps are more pronounced. Government bodies could integrate digital and financial literacy into school and adult education curricula, while financial institutions and NGOs can collaborate to offer hands-on workshops and mobile-based tutorials. Additionally, policymakers might consider developing incentive-based programs that reward individuals for completing digital literacy certifications, especially targeting underserved groups such as women, small entrepreneurs, and older adults. These strategies could help build a more inclusive and resilient digital finance ecosystem, ultimately enhancing the reach and impact of financial inclusion efforts in India.

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# The Role of Psychological and Behavioural Factors in Financial Decision Making: A Quantitative Exploration

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## Abstract

This paper focuses on the effect of behavioural variables of mentality accounting, overconfidence bias, herding behaviour, sensitivity to risk, and aversion to losses on individual investment decisions in India. The results of a quantitative design and statistical test using SPSS (Cronbach's Alpha, ANOVA, regression) show that overconfidence, herding, and loss aversion have a greater impact on investment behaviour, whereas mental accounting and risk sensitivity do not. The findings highlight the influence of psychological biases in making the decisions of investors outside rational models. Such understandings guide financial educators and advice givers to reduce such biases in an attempt to encourage rational and diversified investment behaviour.

**Keywords:** Behavioural Finance, Investment Decision-Making, Psychological Biases, Financial Behaviour, Investor Psychology

## Introduction

India's investment landscape has shifted dramatically over the last decade. Economic expansion, an expanding middle class, and enhanced financial education have all led to a considerable boost in investments across several asset classes. During this period, traditional investment options such as fixed deposits and gold have given way to more diverse portfolios, including equities, mutual funds, real estate, as well as digital assets.

Both of the country's biggest stock exchange, Bombay Stock exchange (BSE), India and National Stock exchange (NSE), India have reflected this trend, recording substantial gains between 2014 and 2024, indicating both increased participation and confidence among Indian investors.

With greater market activity and money flowing into the economy, individuals must manage their finances more efficiently. The expanding opportunities and complexities in the financial sector require meticulous planning and informed decision-making to achieve optimal investment outcomes. The surge in investment activity and the demand for better financial management has resulted in the birth of a new discipline: behavioural finance.

Behavioural finance looks into how individuals fall short of making logical decisions (Hirshleifer, 2015). Behavioural finance investigates the psychological impacts on investors and financial markets, emphasising how and why behaviour frequently deviates from rational expectations. Understanding these discrepancies provides a framework for making better informed and sensible financial decisions (Education, 2021).

Investors differ in many ways based on criteria such as socioeconomic status, education, age, race, and gender. The greatest challenge they deal with is making sound investment choices. Behavioural finance is essential in today's market since it greatly impacts the performance of our investments. Behavioural factors have a significant influence on decision-making; thus, investors must take steps to reduce biases and illusions, particularly in investing decisions (Kannadhasan, 2015).

Emotional biases, cognitive errors, and social factors can cause investors to make illogical decisions, affecting investment performance. In reality, investment decisions are not always made based on rational analysis; they are frequently impacted by psychological aspects known as financial behaviour. Financial behaviour is the study of how psychological, emotional, and social variables influence an individual's financial decision-making.

Despite substantial global study, there is still a lack of understanding about how these behavioural aspects impact investment decisions in India. Existing research tends to concentrate on developed nations, leaving emerging economies largely unexplored. This study bridges the divide by empirically examining the association between important behavioural biases and individual investing decisions in India.

## Literature Review

### Behavioural Finance

Behavioural finance is a reaction to criticism of traditional financial theories through the interdisciplinary approach, which started to appear in the 1980s. It incorporates knowledge in psychology, economics, and cognitive science to describe how investors usually make irrational decisions that do not follow their expected utility and rational models (DeBondt et al., 2010). The discipline disproves rationality, demonstrating that decisions of people are influenced by cognitive shortcuts, emotions, and societal forces (Hirshleifer, 2015).

The study of behavioural finance has repeatedly demonstrated that investors do not utilize the available financial information in a rational manner and are guided by heuristics and biases, which also results in consistent error patterns (Bikas et al., 2013). These biases are the source of market irregularities such as market bubbles, excessive trading, and herd behaviour that could not be described by conventional theories of the Capital Asset Pricing Model (CAPM) and the Hypothesis of Efficient Markets (EMH)(Shefrin, 2001).

### Key Theoretical Foundations

### Efficient Market Hypothesis (EMH)

The EMH theory states that asset prices take into account every pertinent factor meaning that it is unlikely that the performance of the market will be consistent (Baldrige, 2022). This is however challenged by behavioural finance which shows that investors are not all rational processors of information and as a result they are underpriced and inefficient (Timmermann and Granger, 2004; Konstantinidis et al., 2012).

### Expected Utility Theory (EUT)

The first assumption of traditional finance is that expected utility is the way by which people make decisions. However, the practice indicates that in reality, decisions tend to be inconsistent with this principle because of the subjective understanding of the likelihood and value (Schoemaker, 1982; Nawrocki and Viole, 2014).

**Prospect Theory**

Khaneman and Tversky (1979) suggested that people compare the results with a reference point and are more responsive to losses as compared to gains. The principle of loss aversion is the foundation of the modern behavioural finance and the explanation of risk-averse or risk-seeking behaviour based on how the results are framed (Chen, 2024).

**Modern Portfolio Theory (MPT)**

Markowitz (1952) developed modern Portfolio Theory and it states that diversification reduces the risk of a portfolio. Although MPT presupposes reasonable evaluation of risk and returns, behavioural research demonstrates that personal biases including overconfidence and herding may influence the construction of the portfolio (Curtis, 2004).

**Critical Synthesis and Conceptual Linkage**

While traditional finance assumes rational utility maximization, behavioural finance reveals that cognitive biases consistently distort perceptions of risk and return. Studies across contexts suggest that overconfidence, herding, and loss aversion exert strong and measurable influences on investment behaviour, while mental accounting and risk sensitivity often exhibit more nuanced effects. However, empirical evidence from **emerging markets like India** remains limited, especially concerning how these factors interact within local socio-economic and cultural conditions.

**Traditional vs Behavioural Finance**

Behavioural finance investigates how emotions and cognitive biases affect investment decisions. Research indicates that investors regularly make systematic errors, including psychological biases having a considerable impact on market values. These biases also influence public discourse and politics, resulting in a wrong emphasis on popular topics. If people were completely rational, government action might bridge information gaps in capital markets (Muhammad, & Maheran, 2009).

According to efficient markets, traditional theory assumes that investors behave rationally, striving to maximize profit while avoiding risk. However, market peculiarities call into question these assumptions. Behavioural finance came up as an alternative, emphasising the psychological and sociological variables that influence investor decisions and reveal market inefficiencies (Bakshi, 2020).

Traditional finance presumes rational judgements in efficient markets, but actual instances frequently differ. Behavioural finance, which combines psychology and finance, developed to investigate real-world investment decisions made by individuals under real market situations (Vasić et al., 2023).

**Behavioural Factors Affecting Investment Decision-Making**

Research has identified several recurring psychological factors that shape investment behaviour:

- **Mental Accounting:** Thaler (1999) found that individuals categorize money into separate "mental accounts," leading to inconsistent financial choices. Although this simplifies decision-making, it may cause investors to overlook portfolio-level risks (Segal, 2024).
- **Overconfidence Bias:** Investors at times misjudge their understanding or prediction accuracy, which leads to excessive trading and poorly diversified portfolios (Vipond, 2024; Skala, 2008).

- **Herding Behaviour:** Bikhchandani and Sharma (2001) demonstrated that individuals often imitate others' actions, particularly under uncertainty, amplifying market volatility.
- **Risk Sensitivity***:* People differ in their tolerance for uncertainty. While some avoid risk, others embrace it under certain framing conditions, influenced by cognitive and emotional factors (Davies & Satchell, 2006; Stefánsson & Bradley, 2019).
- **Loss Aversion:** In accordance with prospect theory, investors respond proactively to losses than similar returns, resulting in unduly cautious or delayed selling activity (Khan, 2017; Kumar & Babu, 2018).

## Objectives Of The Study

- To investigate the influence of mental accounting on one's financial decision-making.
- To study how overconfidence bias affects investment choice.
- To assess the task of herd behaviour in influencing investment decisions.
- To examine how risk sensitivity influences investment choices and decision-making processes.
- To investigate how loss aversion effects individuals' investment decisions.

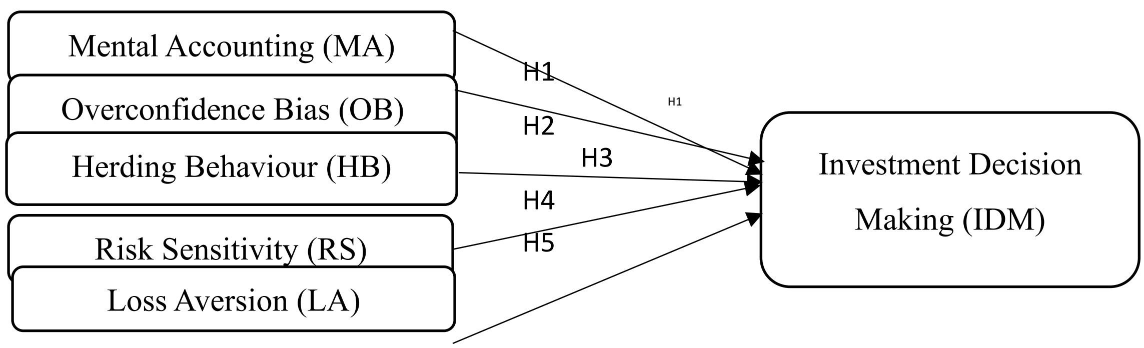


**Figure 1: Research Framework**

## Hypothesis Formulation

H1: Mental accounting significantly influences investment decision-making among individuals.
H2: Overconfidence bias significantly affects investment decision-making among individuals.
H3: Herding behaviour significantly affects investment decision-making among individuals.
H4: Risk sensitivity significantly affects investment decision-making among individuals.
H5: Loss aversion significantly affects investment decision-making among individuals.

## Research Methodology

This investigation used a quantitative research approach to evaluate the behavioural factors that influence individual investment choices in India. The primary information was obtained in a well-organised survey among individuals who were actively engaged in investment operations. The research aimed at measuring the associations among major behavioural variables, such as, mental accounting, overconfidence bias, herding behaviour, risk sensitivity, and loss aversion, and the overall investment behaviour.

Stratified random sampling method was used to achieve the consideration of important demographic factors of age, gender, income, and education level. The total number of valid responses received was 348 with people in the urban and semi-urban areas. A sufficient statistical power and generalizability of findings were established by determining the sample size.

This questionnaire was divided into two parts. Section A involved the collection of demographic information and Section B involved assessing the behavioural and psychological variables on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Each construct was accessed using measurement items that were derived and modified based on the published scales in literature on behavioural finance with a guarantee of reliability and content validity. The survey questionnaire underwent a pre-test on 20 respondents in order to ease the wording and clarity. The comments resulted in slight modifications to increase interpretability.

Behavioural factors (mental accounting, overconfidence, herding, risk sensitivity, and loss aversion) were the choice of independent variables, and investment decision-making used as the dependent variable. The control variables that supposedly explain the presence of external factors were the demographic factors (age, gender, and education level).

The Cronbach Alpha of each construct was calculated to determine the consistency of measurement. A value of above 0.7 was deemed acceptable, and it ensured a good internal reliability. Even though some of the constructs (mental accounting and risk sensitivity) lacked reliability, they were not dropped out of consideration due to their theoretical importance and available empirical history. The established scales were used to ensure content validity, and the pre-testing was used to test face validity.

The information gathered was examined using SPSS analytical software. Descriptive data analysis was employed for describing respondent characteristics and behavioural features. Inferential statistics were used to test hypotheses and assess the overall effects of behavioural variables on investment decision-making by ANOVA and multiple regression. The application of ANOVA proved to be adequate since it allowed to determine the overall model significance and the variance explained by several predictors. Also, multiple regression coefficients gave information on the relative significance of each behavioural variable. Before the inferential analysis, assumptions of normality, linearity, multicollinearity and homoscedasticity were examined. There was no gross violation of the statistical model as no serious violation was detected.

Informed consent was obtained by all of the participants, and the responses were made confidential. The collection of the data was carried out according to the normal ethics of an academic research, where there is voluntary participation and anonymity.

## Results and Discussion

In Table 1, the socioeconomic characteristics of those who participated was shown, predominantly young (59.48% under the age of 25) and male (57.76%), with limited investment experience (59.48% having less than one year). Mutual funds emerged as the preferred investment choice (35.34%), followed by fixed deposits (20.69%) and equities (18.1%), indicating a preference for stable and diversified investments over higher-risk alternatives.

**Table 1: Demographic Characteristics**

| *Characteristic* | | *Frequency* | *Percentage (%)* |
|---|---|---|---|
| Age | < 25 years old | 207 | 59.48 |
| | 26-35 years old | 105 | 30.17 |
| | 36-45 years old | 9 | 2.59 |
| | 46-55 years old | 12 | 3.45 |
| | > 56 years old | 15 | 4.31 |
| | Total | 348 | 100 |
| Gender | Male | 201 | 57.76 |
| | Female | 147 | 42.24 |
| | Total | 348 | 100 |
| Education Level | High School | 9 | 2.59 |
| | Bachelor's Degree | 139 | 37.07 |
| | Master's Degree | 204 | 58.62 |
| | Doctorate | 6 | 1.72 |
| | Total | 348 | 100 |
| Investment Experience | < 1 year | 207 | 59.48 |
| | 1-3 years | 75 | 21.55 |
| | 3-5 years | 30 | 8.62 |
| | 5-10 years | 24 | 6.9 |
| | > 10 years | 12 | 3.45 |
| | Total | 348 | 100 |
| Investment Portfolio | Mutual Funds | 123 | 35.34 |
| | Fixed Deposit | 72 | 20.69 |
| | Equities | 63 | 18.1 |
| | Real Estate | 15 | 4.31 |
| | Government Bonds | 6 | 1.72 |
| | Others | 69 | 19.83 |
| | Total | 348 | 100 |

Table 2 (Annexures) illustrates that individuals exhibit moderate mental accounting behaviours, reflected by an average score of 3.58. This indicates a propensity to delineate their finances, evaluating decisions based on individual account balances instead of total wealth. Notably, specific behaviours such as the routine monitoring of savings account expenditures are prevalent, as evidenced by the elevated mean scores in these categories.

Table 3 (Annexures) indicates that respondents display moderate levels of overconfidence bias, with an average score of 3.16. This implies that, although overconfidence is evident, it is not uniformly present among all participants.

Table 4 (Annexures) illustrates a moderate inclination towards herding behaviour among participants, with an average score of 3.16. The influence of social factors is significant, as indicated by a high average score of 3.45 for reliance on personal networks. However, the lower average score of 2.82 for modifying investments in response to differing decisions made by others suggests a degree of decision-making autonomy.

Table 5 (Annexures) indicates that individuals demonstrate a pronounced sensitivity to risk, with an average score of 3.58. The elevated scores for preferring low-risk, stable-return investments (3.70) and adjusting strategies in accordance with risk tolerance (3.63) suggest a risk-averse profile. Nevertheless, a moderate score (3.50) in relation to avoiding high-risk investments indicates a willingness to embrace risks for the potential of attractive returns.

Table 6 (Annexures) illustrates that individuals demonstrate pronounced loss aversion, with an average score of 3.33. Participants emphasize the importance of minimizing losses over maximizing gains (mean = 3.57), aligning with the principles of prospect theory. A diminished mean for liquidating investments at a loss (3.00) signifies a hesitation to accept losses, possibly due to expectations of recovery or emotional attachments. The low standard deviation reflects a strong agreement regarding loss-avoidance behaviour.

Table 7 presents a reliability analysis using Cronbach's Alpha for the behavioural variables. The findings indicate a strong internal consistency across all variables, with the exception of risk sensitivity, which demonstrates a lower level of reliability.

**Table 7: Reliability Test**

| *Variables* | *Number of Items* | *Mean* | *SD* | *Cronbach's Alpha* |
|---|---|---|---|---|
| Mental Accounting | 5 | 3.58 | 0.929 | 0.539 |
| Overconfidence Bias | 5 | 3.16 | 0.909 | 0.705 |
| Herding Behaviour | 5 | 3.16 | 0.957 | 0.751 |
| Risk sensitivity | 5 | 3.58 | 0.903 | 0.335 |
| Loss Aversion | 5 | 3.33 | 0.915 | 0.66 |

Table 8 illustrates a commendable level of overall reliability for the model assessing behavioural factors that influence investment decisions, as indicated by a Cronbach's Alpha score of 0.741, surpassing the acceptable threshold of 0.7. This score signifies strong internal consistency among the variables, thereby reinforcing the model's relevance in exploring the relationships among mental accounting, overconfidence bias, herding behaviour, risk sensitivity, and loss aversion. While minor irregularities in individual variables are noted, the model effectively encapsulates key behavioural elements, thereby corroborating the methodology employed in the study.

**Table 8: Overall Reliability Statistic**

| *Cronbach's Alpha* | *Overall Model* |
|---|---|
| 0.741 | Reliable |

Table 9 shows the outcomes of the ANOVA study, which verify the framework's statistical significance for measuring behavioural elements and decision-making regarding investments. The predictive model's F-value of 5.771 and p-value of 0.000 ($p < 0.05$) indicate that each of the independent factors—mental accounting, overconfidence bias, herding behaviour, risk sensitivity, and loss aversion—have an important impact on investment conduct.

The regression Sum of Squares (336.309) measures the variance in investment decisions revealed by the statistical model, whereas the residual Sum of Squares (750.622) represents unaccounted variability caused by components not addressed in the examination. This suggests that, while the model adequately explains a significant portion of the diversity in investment behaviour, there are still other factors that are unaccounted for. The broad relevance of the model stresses the importance of behavioural elements in determining investment decisions.

**Table 9: ANOVA**

| *ANOVA*[a] | | | | | | |
|---|---|---|---|---|---|---|
| ***Model*** | | ***Sum of Squares*** | ***df*** | ***Mean Square*** | ***F*** | ***Sig.*** |
| 1 | Regression | 336.309 | 25 | 13.452 | 5.771 | .000[b] |
| | Residual | 750.622 | 322 | 2.331 | | |
| | Total | 1086.931 | 347 | | | |

a. Dependent Variable: Investment Behaviour

b. Predictors: (Constant), LA5, RS4, MA5, OB5, OB2, MA4, MA2, HB5, OB3, RS2, HB1, LA3, RS3, MA1, RS1, MA3, HB4, LA2, RS5, LA4, OB4, HB2, HB3, OB1, LA1

Table 10 shows the findings of testing for hypothesis, which assesses the particular effect of each behavioural aspect on investing decisions. The level of statistical significance was established using p-values, which indicate which behavioural components have a significant impact on investment behaviour.

**Table 10: Hypothesis Test**

| | ***Hypothesis*** | ***p-values*** | ***Result*** |
|---|---|---|---|
| $H_1$ | Mental accounting significantly influences individual investment decision-making | >0.01 | Rejected |
| $H_2$ | Overconfidence bias has a considerable effect on the investment behaviour of individuals | <0.01 | Accepted |
| $H_3$ | Herding behaviour markedly impacts the investment decisions of individuals | <0.01 | Accepted |
| $H_4$ | Risk sensitivity plays a crucial role in shaping the investment preferences of individuals | >0.01 | Rejected |
| $H_5$ | Loss aversion considerably affects the investment decisions made by individuals | <0.01 | Accepted |

The outcomes of the hypothesis assessment provide data on how behavioural aspects impact the choice of investments. The study findings showed that three hypotheses (H 2, H 3, and H 5) were confirmed, which are: overconfidence bias, herding behaviour, and loss aversion, whilst the mental accounting (H 1 ) and risk sensitivity (H 4 ) were insignificant as indicated in Table 2. The above results suggest that the role of emotional and social bias on investor decision-making is more significant than cognitive compartmentalization and risk aversion.

Rejection of H1 is contrary to previous studies by Thaler (1999) and Segal (2024) who reported that mental accounting causes irrational decisions. Such behaviour, however, in this study seems to meet some practical budgeting purpose other than playing out as a bias. This may be attributed to the cultural background of collective family decision-making and conservative financial behaviour of the Indian investors.

Acceptance of H2 proves that overconfidence does play a major role in investment behaviour in line with the previous research (Skala, 2008; Vipond, 2024). More common among less experienced and younger investors is overestimating their capabilities and increasing their risk exposures and trading. Likewise, H3, the herding behaviour turned out to be a powerful predictor of investment decisions, as was the case with Bikhchandani and Sharma (2001). Peer decisions and the sentiment in the market seem to have a strong effect on investors and social media and online investing tools only tend to strengthen this trend.

The rejection of H4 indicates that risk sensitivity is not a sole determinant of investment. The result is contrary to that of Davies and Satchell (2006), which could be attributed to the fact that there was not much variation in risk tolerance among respondents, as they were mostly young and risk-averse. H5 (loss aversion) on the other hand, was significantly positively associated with the investment choices, which are in favor of prospect theory (Kahneman and Tversky, 1979). Investors have a strong desire to prevent losses, which is consistent with past research (Kumar and Babu, 2018).

## Conclusion

The study investigated how behavioural characteristics such as mental accounting, biases regarding overconfidence, herding behaviour, risk sensitivity, and fear of loss influence Indian investors' investing decisions. The findings show that overconfidence, herding, and loss aversion have a considerable impact on investor conduct, while mental accounting and risk sensitivity have no statistical significance. These findings reinstate the fact that investment decisions are influenced more due to psychological and social biases than logical considerations.

The prevalence of emotional aspect in young and inexperienced investors underscores the significance of behavioural awareness in enhancing better financial judgement. The model had a good reliability (= 0.741) and moderate explanatory power (Adjusted R2 = 0.30), therefore it can be recommended to add some other behavioural or contextual variables in future research.

The research also contributes to the academic sphere of knowledge, providing evidence of an emerging market, indicating that the effects of behavioural biases may be different in cultural and demographical backgrounds. In practice, it highlights the necessity of biased advisory model and investor education that can deal with overconfidence, herding and loss aversion. The behavioural financing principles should be incorporated in investor awareness programs and training programs by regulators like SEBI and financial institutions.

## Scope for Future Research

This research examines future areas for investigation. It aims to analyze the interaction between mental accounting, risk sensitivity, and demographic or market-specific factors to gain a deeper understanding of their implications. Expanding the structure to include biases such as bias towards availability, anchored bias, and regretful avoidance may increase the model's ability for analysis. Additionally, cross-cultural studies could explore regional variations in behavioural biases, potentially leading to tailored, region-specific solutions that enhance global financial decision-making.

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# Annexures

**Table 2: Responses towards Mental Accounting**

| ***Item*** | ***Statement*** | ***Mean*** | ***SD*** |
|---|---|---|---|
| MA1 | I divide my money into many accounts and manage it separately | 3.69 | 0.961 |
| MA2 | I closely manage my savings account expenditures | 3.87 | 0.858 |
| MA3 | I make decisions based on individual account balances rather than the total sum | 3.45 | 0.924 |
| MA4 | I avoid combining funds from different accounts, even if it is helpful | 3.40 | 0.799 |
| MA5 | I spend more money on unexpected income, such as bonuses, than on normal wages | 3.47 | 1.104 |
| | Average Score of Mental Accounting | 3.58 | 0.929 |

**Table 3: Responses towards Overconfidence Bias**

| *Item* | *Statement* | *Mean* | *SD* |
|---|---|---|---|
| OB1 | I feel I can predict market movements better than the typical investor | 2.90 | 0.979 |
| OB2 | I overestimate my capacity to select profitable assets | 3.13 | 0.827 |
| OB3 | I am certain that my financial decisions consistently produce excellent results | 3.58 | 0.833 |
| OB4 | I believe my investment talents are superior to those of my colleagues | 3.18 | 0.917 |
| OB5 | I rarely rethink my investing selections, even after a loss | 3.03 | 0.988 |
| | Average Score of Overconfidence Bias | 3.16 | 0.909 |

**Table 4: Responses towards Herding Behaviour**

| *Item* | *Statement* | *Mean* | *SD* |
|---|---|---|---|
| HB1 | I follow the market behaviours of others, presuming they have greater information | 3.14 | 0.947 |
| HB2 | I invest in assets that are popular with other investors | 3.07 | 1.050 |
| HB3 | When others make different decisions, I modify my investments accordingly | 2.82 | 1.049 |
| HB4 | I feel comfortable investing in alternatives that are extensively endorsed by others | 3.34 | 0.852 |
| HB5 | I base my financial selections on trends or advice from personal networks | 3.45 | 0.885 |
| | Average Score of Herding Behaviour | 3.16 | 0.957 |

**Table 5: Responses towards Risk Sensitivity**

| *Item* | *Statement* | *Mean* | *SD* |
|---|---|---|---|
| RS1 | I avoid high-risk investments, even if the prospective returns are equally high | 3.50 | 0.980 |
| RS2 | I choose low-risk investments that provide consistent but lesser returns | 3.70 | 0.959 |
| RS3 | I take financial risks when the return potential is large | 3.53 | 0.952 |
| RS4 | I'm more worried about losing money than missing out on prospective rewards | 3.53 | 0.934 |
| RS5 | I alter my methods based on risk tolerance, not market developments | 3.63 | 0.690 |
| | Average Score of Risk Sensitivity | 3.58 | 0.903 |

**Table 6: Responses towards Loss Aversion**

| *Item* | *Statement* | *Mean* | *SD* |
|---|---|---|---|
| LA1 | I prioritise avoiding losses above maximising gains | 3.57 | 0.824 |
| LA2 | I rapidly sell investments at a loss to avoid prospective recoveries | 3.00 | 1.010 |
| LA3 | I hang onto losing investments to avoid incurring a loss | 3.23 | 0.978 |
| LA4 | Fear of losing money has a huge impact on my financial selections | 3.48 | 0.887 |
| LA5 | I take chances to avoid losses rather than to make profits | 3.38 | 0.879 |
| | Average Score of Loss Aversion | 3.33 | 0.915 |

## Questionnaire

1. **Age:**
    - 18-25
    - 26-35
    - 36-45
    - 46-55
    - 56 and above
2. **Gender:**
    - Male
    - Female
    - Other
3. **Education Level:**
    - High School
    - Bachelor’s Degree
    - Master’s Degree
    - Doctorate
    - Other
4. **Monthly Income (in INR):**
    - Less than ₹25,000
    - ₹25,000-₹50,000
    - ₹50,000-₹75,000
    - ₹75,000-₹1,00,000
    - More than ₹1,00,000
5. **Investment Experience:**
    - Less than 1 year
    - 1-3 years
    - 3-5 years
    - 5-10 years
    - More than 10 years
6. **Primary Investment Type:**
    - Equities
    - Mutual Funds
    - Real Estate
    - Fixed Deposits
    - Government Bonds
    - Other

**Behavioral Variables Questions (Likert Scale Options: Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree)**

**Mental Accounting:**

1. **I categorize my money into different "accounts" (e.g., savings, spending) and treat them differently**.
    - Strongly Disagree
    - Disagree

- Neutral
- Agree
- Strongly Agree

2. **I pay more attention to how I spend money from my savings account than from my daily spending.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree
3. **I often make decisions based on how much I have in different accounts, even if the total amount is the same.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree
4. **I avoid mixing funds from separate accounts, even when it might make sense to do so.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree
5. **I find myself spending more when I receive unexpected money, such as bonuses or refunds, compared to my regular income.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree

**Overconfidence Bias:**

6. **I believe I am better at predicting market trends than the average investor.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree
7. **I tend to overestimate my ability to choose profitable investments.**
   - Strongly Disagree
   - Disagree
   - Neutral
   - Agree
   - Strongly Agree
8. **I am confident that my financial decisions will consistently lead to positive results**.
   - Strongly Disagree

- Disagree
- Neutral
- Agree
- Strongly Agree

**9. I believe my investment skills are superior to those of my peers.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**10. I rarely doubt my own investment decisions, even after a loss.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**Herding Behavior:**

**11. I often follow what others are doing in the market, assuming they have better information.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**12. I am likely to invest in a particular stock or asset if I see many others doing the same.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**13. I change my investment decisions when I find out that others are making different choices.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**14. I feel more confident when I invest in something that others are also investing in.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**15. I have made investment decisions based on trends or advice from friends, family, or social networks.**

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**Risk Sensitivity:**

**16. I avoid investments that have a high potential for loss, even if the rewards are equally high.**
- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**17. I prefer low-risk investments that offer steady returns, even if they are smaller.**
- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**18. I am willing to take financial risks if I believe the potential for profit is high.**
- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**19. I worry more about losing money than missing out on potential gains.**
- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**20. I adjust my investment strategies based on how much risk I am comfortable with, rather than market trends.**
- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

**Loss Aversion:**

**21. I am more concerned about avoiding losses than making profits.**
- Strongly Disagree
- Disagree
- Neutral
- Agree

- Strongly Agree

22. **I tend to sell investments quickly when they show a loss, even if it means missing a potential recovery.**
    - Strongly Disagree
    - Disagree
    - Neutral
    - Agree
    - Strongly Agree
23. **I hold on to losing investments for too long because I do not want to realize the loss.**
    - Strongly Disagree
    - Disagree
    - Neutral
    - Agree
    - Strongly Agree
24. **The fear of losing money influences most of my investment decisions.**
    - Strongly Disagree
    - Disagree
    - Neutral
    - Agree
    - Strongly Agree
25. **I am more likely to take risks to avoid a loss than to achieve a gain.**
    - Strongly Disagree
    - Disagree
    - Neutral
    - Agree
    - Strongly Agree

# Sustainable Tax Savings for Eco-Friendly Taxpayers in the Urban Capital: An Analytical Approach

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## Abstract

The ‘Government of India’ has called for 'only Electric Vehicles' on the Road by 2030, encouraging people to switch to EVs. Keeping this in mind and the need for research in this area, this paper aims to identify and examine the potential tax savings that households in Delhi, India, can achieve through eco-friendly commuting behaviours such as electric vehicles (EVs), public transports Like carpooling and Metros. The objectives are to see the impact of fuel consumed and tax savings on pollution emission and to see the worldwide collaboration to get the overview of India, further how switching to public transport can be helpful leading to the creation of policies that can encourage an individual to do such practices, which can be helpful for the economy and the environment. This paper analysed the role of Household income as mediating factors, inter-relationship between all the variables. The methods used are the statistical Structural Equation Modelling (SEM), Regression, R- studio and Biblioshiny. The findings show that EV adoption, Carpooling and public transport usage can significantly reduce fuel consumption. Further, Fuel consumption and tax savings does have a significant impact on pollution emission after switching to greener options available. It is also concluded that the benefits are distributed unevenly across different income groups, which should be included in tax-saving schemes regarding tax rebates to promote more such sustainable practices. Higher-income households tend to benefit more from EV-related tax incentives, owing to their ability to afford the high upfront costs of EVs. In contrast, those more likely to rely on public transport or carpooling save money from fuel-efficient commuting practices but miss out on the more enormous subsidies available for EV ownership. The findings prove valuable for Policymakers and concerned stakeholders in increasing subsidies and giving financial support, encouraging EV adoption, expanding tax benefits for public transport users and car-poolers, and implementing awareness campaigns to ensure a broader understanding of eco-friendly commuting benefits.

**Keywords**: Electric Vehicles, Public-Private Transport, Tax Savings, Emission, Sustainability, R-Studio Regression, SEM, Biblioshiny.

## Introduction

This study examines the potential tax savings households in Delhi, India, can achieve through eco-friendly commuting behaviour, such as adopting electric vehicles (EVs) and using public transport like Metro, Public buses, and carpooling. Using regression, the study explores how household income, fuel consumption, government subsidies, and carbon credit incentives induce tax savings and pollution Emissions. The study further looks into the role and strength of the relationships between Fuel consumption and tax savings on Pollution emissions. Climate change represents a critical challenge for humanity today, with environmental degradation profoundly impacting ecosystems, economies, and public health across the globe, with the most severe impacts in low- and middle-income countries. Major urban centres such as Beijing, Los Angeles, and Mexico City have faced significant air quality challenges, necessitated immediate action and implemented sustainable measures to mitigate emissions and enhance public health.

Transportation plays a pivotal role in urban air pollution, as vehicle emissions release considerable amounts of PM, NOx, and VOC into the atmosphere. The reliance on fossil fuel-powered vehicles exacerbates this issue, resulting in elevated greenhouse gas emissions and heightened risks to public health. Numerous strategies have been adopted worldwide to promote cleaner transportation alternatives in response to these urgent concerns. Among these initiatives, carbon credit schemes have emerged as a vital mechanism for incentivizing reductions in carbon emissions. Carbon credits represent a market-driven approach to mitigating pollution by offering financial incentives to entities and individuals to reduce their carbon emissions. Entities can earn credits by lowering emissions below a predetermined cap, which can be sold or traded in carbon markets. For example, a manufacturing firm investing in energy-efficient technologies may significantly reduce carbon emissions. This reduction is quantified, and the corporation receives carbon credits that can be sold to other businesses struggling to meet their emissions targets. Such mechanisms encourage investment in clean technologies and provide financial rewards for effective emissions reduction. Countries like Sweden and the European Union have adopted carbon trading systems with notable success in improving air quality and reducing greenhouse gas emissions. In India, the government has initiated policies to encourage sustainable transportation, primarily focusing on EV adoption as a cleaner alternative to conventional vehicles. With ambitious targets to transition to an EV-dominated fleet by 2030, the Indian government has introduced various incentives, including tax deductions, subsidies, and reduced GST rates, making EVs more affordable and accessible to consumers.

However, while EVs represent a substantial step forward in reducing emissions, they come with their challenges. Additionally, the increased demand for electricity to charge EVs strains existing power grids, mainly where electricity is generated from fossil fuels, potentially offsetting some benefits of switching to electric vehicles. High initial costs, limited charging infrastructure, and resource scarcity also present obstacles to widespread EV adoption, particularly for low- and middle-income individuals who may find EVs financially inaccessible.

Furthermore, the focus on E.V.s often overshadows the contributions made by public transportation and carpooling in reducing urban emissions. Public transit and shared rides significantly lower per capita emissions than personal motor spirit use, including electric vehicles. In heavily polluted cities like Delhi, fossil fuel-powered personal motor spirit use remains prevalent despite existing tax incentives, highlighting the need for a more inclusive approach to sustainable transportation. Extending tax incentives to public transport users and car-poolers could encourage more sustainable commuting habits, reducing reliance on personal motor spirits. For example, commuters using metro systems or buses could receive tax credits for their reduced carbon footprint, and car-poolers could claim deductions based on their shared mileage.

This study investigates the potential of offering financial incentives to public transport users and car-poolers to reduce urban pollution. By exploring tax breaks and similar measures, this research promotes an equitable, sustainable approach to emissions reduction, supporting inclusive transportation solutions. While E.V.s provide essential environmental benefits, this research argues that a comprehensive strategy, including incentives for all sustainable transport modes, is necessary to achieve meaningful and equitable pollution reductions. Ultimately, this study seeks to provide policymakers with evidence-based recommendations to develop tax incentives encouraging diverse, sustainable commuting choices, contributing to cleaner urban environments and improved public health in heavily polluted areas.

Rest part contains: The literature which is in the second section, third part is about research technique applied in this study, followed by results, analysis, discussion and implications. Last section consist of conclusion, limitations and future scope.

## Literature Review

Emerging environmental issues are raising awareness about sustainability (Rahman, 2023). In the modern context, sustainability has evolved from being an option to a necessity for fostering an environmentally responsible planet. This transformation demands stringent legislation, effective enforcement, and robust justice mechanisms (*GREEN TAXATION : PROMOTING ENVIRONMENT SUSTAINABILITY*, 2023). Taxation policies are now widely recognized as pivotal instruments for driving sustainable economic growth (Liko & Shahini, 2023) and "The Impact of Government Incentives on Hybrid Vehicle Adoption" aimed to assess how government incentives, including subsidies, tax credits, and rebates, influence the adoption of hybrid vehicles across various income groups in the United States (Diamond, 2009). The problem focused on whether these incentives effectively promoted adoption among lower-income households or primarily benefited wealthier groups. The research found that while government incentives were successful in increasing hybrid vehicle sales overall, lower-income households were less likely to benefit due to high upfront vehicle costs, even with subsidies. (Diamond, 2009) recommended increasing the value of subsidies for low-income families and providing additional financial support mechanisms, such as low-interest loans, to promote broader adoption. An individual can plan and study saving schemes to understand (Bhawar & Shirsath, 2018) even Sustainable Tax Strategies can lead to a Persistent earnings of a firm (Adolph, 2016).

Sustainable commuting, which is an Integral part of SDGs (Bhattacharyya et al., 2022) and there are multiple sustainable commuting systems available, SC usually refers to environmentally friendly travel modes, such as public transport (bus, tram, subway, light rail), walking, cycling, and carpooling (Molina et al., 2020). Smart carpooling services may be an alternative and enrichment for mobility, which can help smart cities (SCs) reduce traffic congestion and gas emissions (Anthopoulos & Tzimos, 2021). Recent changes in carpooling, such as carpooling platforms and apps, and changes in lifestyles that may affect carpooling practices, such as telework (Aguiléra & Pigalle, 2021). Carpooling that emphasizes on a shared use of private cars, would increase by 30 percent and this increase will reduce annual fuel consumption about 240 million litres (Seyedabrishami et al., 2012). Different carpooling solutions can represent the potential to make a valuable contribution to making urban mobility more sustainable and support a new culture of car use (Bresciani et al., 2018). EV which is a sustainable option (Buhmann et al., 2024; Habib

& Lynn, 2020; Higueras-Castillo et al., 2023; Jayasingh et al., 2021; Jung Moon, 2020; Sanchez-Iborra et al., 2020). EVs, globally are being promoted as an eco-friendly transport option and as a potential solution (Bhattacharyya et al., 2022). Environmental concerns caused due to fossil fuel depletion and greenhouse gas (GHG) emissions has paved way for consumers to consider EV (Jaiswal, 2023; Michael et al., 2022). (Sierzchula et al., 2014), in their paper "Factors Influencing EV Adoption, the study examined the factors that influence the adoption of electric vehicles (EVs) in 30 countries, with a specific focus on government incentives like subsidies and their effect across different income levels. The change from private vehicle to sustainable commuters option can not only lead to reduction in fuel consumption but also be helpful in saving of household income, as per (Papagiannakis et al., 2018), if the individuals have reduced the trip frequency by private car, or they have shifted to public transport for downtown trips, In some cases, this reduction in expenses led to household relocation.

In the Indian context, (Bhattacharyya et al., 2022; Jaiswal, 2023) noted that EV adoption is driven by concerns over fossil fuel dependency and greenhouse gas emissions. (Michael et al., 2022) found that increasing environmental awareness is improving adoption rates in Indian cities. (Kumar & Bangwal, 2023) demonstrated that public transport use significantly reduces fuel consumption, emissions, and traffic congestion. (Ghosh & Varma, 2021) identified the positive effect of tax incentives, particularly Section 80EEB of the Indian Income Tax Act, which allows interest deductions on EV loans. These schemes lower the financial burden on middle-class adopters and can be expanded further to reach economically weaker sections. Metro rail and electric buses offer high-capacity, low-emission alternatives for urban areas (Sharma & Singh, 2022). (Mehta., 2021) projected that metro system expansion could reduce urban air pollution by over 20% within five years. Jha & Narayan (2020) highlighted carpooling's dual role in fuel savings and behavioural change, reinforcing the importance of multi-modal policy support. Recent empirical work by (Verma et al., 2023) used structural equation modelling (SEM) to show that fuel consumption mediates the relationship between commuting choices, tax savings, and emissions. (Roy & Chatterjee, 2021) identified income as a moderator, indicating that households with lower income levels are more responsive to financial incentives. SEM-based studies by (Zope et al., 2022), and researchers in *Frontiers in Sustainability* (2022) reinforce that user perception, access, policy awareness, and affordability are pivotal to behavioural shifts. Policy reviews by Indian agencies like NITI Aayog (2020) and MoEFCC (2020) echo these findings. Both recommend targeted strategies such as employer-supported commuting allowances, direct EV subsidies, maintenance grants, and differential tax benefits based on income. These interventions are designed to overcome affordability gaps and shift long-term behaviour.

The selection of the three variables—fuel consumption, tax savings, and pollution emissions—is grounded in existing research and policy evaluations that highlight their critical roles in assessing the impact of sustainable commuting choices and government interventions. These variables together enable a multi-dimensional understanding of resource efficiency, fiscal influence, and environmental outcomes. Fuel consumption serves as a direct and measurable indicator of resource utilization in transportation. It reflects the intensity of fossil fuel dependence and is sensitive to changes in commuting behaviour such as shifts to electric vehicles (EVs), public transport, or carpooling. According to (Verma et al., 2023), fuel consumption plays a mediating role in determining the link between commuting patterns and tax savings, making it a crucial component in structural models evaluating eco-friendly behaviour. Similarly, (Choudhary et al., 2022) demonstrated that public transport usage significantly reduces fuel demand, leading to lower emissions. Tax incentives are one of the key policy instruments used to promote sustainable commuting. These include interest deductions on EV loans (e.g., Section 80EEB of the Indian Income Tax Act), subsidies, and exemptions. (Ghosh & Varma, 2021) highlighted how such fiscal policies directly impact the affordability of EVs, particularly for middle-income households. (Verma et al., 2023) emphasized that tax savings not only reflect the effectiveness of policy incentives but also serve as a financial motivation for behavioural change among commuters. Thus, incorporating this variable helps capture the economic lever governments use to reduce carbon-intensive transport. Pollution emissions are the ultimate environmental outcome variable, enabling researchers to assess whether behavioural and policy-driven interventions translate into tangible environmental benefits. (Sharma & Singh, 2022) reported that adopting metro and electric bus systems leads to significant emission reductions in Indian cities. Moreover, (Jha & Narayan, 2020) illustrated that carpooling results in measurable reductions in air pollutants. These studies reinforce that emissions data—measured before and after sustainable transitions—offers a robust basis for evaluating environmental improvement. These three variables also align with recent SEM-based studies (Zope et al., 2022; Soti et al., 2023), which assess how perceptions, access, and affordability influence sustainable transport outcomes. The interconnectedness of fuel usage, tax incentives, and emissions forms a coherent model to assess both individual behavioural shifts and macro-level policy impacts.

The researchers concluded that financial incentives, including purchase subsidies and tax breaks, were critical drivers for increasing EV adoption. However, they noted that lower-income households benefited less from these incentives compared to higher-income groups, primarily due to the high upfront costs of EVs. (Jenn et al., 2018) "EV Subsidy Effectiveness in California" focused on evaluating the effectiveness of California's subsidies for electric vehicles, particularly the Clean Vehicle Rebate Project (CVRP), in promoting EV adoption among lower-income households. The problem identified was the underutilization of subsidies by low-income households and whether these incentives could reduce inequality in EV adoption. The study found that while subsidies significantly increased overall EV adoption, low-income households faced barriers such as high upfront costs and problem with infrastructure (e.g., charging stations in low-income neighbourhoods). The authors recommended increasing the rebate amount for low-income households and improving charging infrastructure in underserved areas to enhance the effectiveness of the subsidy program. As per (Carley et al., 2017) the Unequal Distribution of EV Subsidies**,** explored how subsidies for electric vehicles are distributed among income groups in the United States. Low-income households were less likely to take advantage of subsidies due to financial and infrastructure barriers. (Li et al., 2017), examined the impact of China's EV subsidy policies on adoption rates, with a focus on understanding whether the subsidy structure effectively encouraged low- and middle-income households to switch to electric vehicles, the study found that the purchase subsidies in China had a significant impact on overall EV adoption, but low-income households were still underrepresented among adopters due to affordability concerns. (Mersky et al., 2016) says, subsidies and charging Infrastructure Impact on EV Adoption in Norway. The study concluded that the combination of generous subsidies and well-developed charging infrastructure was essential for Norway's success in promoting EV adoption. The authors recommended further expansion of infrastructure in low-income areas and increased subsidies for these groups. (De Rubens et al., 2018), Policy Impact on EV Adoption in Europe**,** analysed how various policy measures, including subsidies and tax rebates, affected EV adoption rates across European countries, with a specific focus on how income inequality affected access to these benefits.

These sustainable commuters are not just helpful in reducing pollution but also will be saving tax. At last, Sustainable commuting options such as electric vehicles (EVs) and carpooling significantly reduce fuel consumption by decreasing the reliance on conventional fossil fuels. EVs operate on electricity, which eliminates the need for petrol or diesel, while carpooling allows multiple people to share a single vehicle, cutting down the number of cars on the road and thereby reducing overall fuel usage. This not only helps in conserving natural resources but also minimizes carbon emissions, contributing to a cleaner environment. Additionally, many governments offer tax benefits and incentives to promote sustainable transport—such as reduced registration fees, income tax deductions, or subsidies for EV purchases—enabling commuters to save money while supporting eco-friendly practices.

## Objectives

The study aims to assess the potential tax savings that households in Delhi can achieve through eco-friendly commuting behaviour, specifically focusing on the disparity in benefits between electric vehicle (EV) users and those who rely on public transport or carpooling.

1. Assess the direct, indirect, and moderating relationships among commuting behaviour variables (EV adoption, public transport usage, carpooling, distance travelled, household income, and fuel consumption) and their collective impact on tax savings using SEM.
2. To examine the impact of fuel consumption on pollution emissions before to the adoption of eco-friendly commuting practices (associated with H1).
3. To analyse the effect of tax savings on pollution emissions before the switch to sustainable commuting modes (associated with H2).
4. To assess the effect of fuel consumption on pollution levels after adopting eco-friendly alternatives such as EVs, public transport, or carpooling (associated with H3).
5. To examine the relationship between tax savings and pollution emissions after the adoption of sustainable commuting modes (associated with H4).
6. To analyse trends in published literature across different countries, focusing on collaborative efforts and emerging themes related to eco-friendly commuting and policy incentives.
7. This research offers policy suggestions for designing inclusive tax incentives that encourage the use of EVs, public transport, and carpooling—especially for households currently lacking such benefits.

## Hypothesis

H1: Fuel consumed has a significant impact on pollution emission before switching.
H2: Tax savings have a significant impact on pollution emissions before switching.
H3: Fuel consumed does have a significant impact on Pollution emissions after switching.
H4: Tax savings have a significant impact on pollution emissions after switching.

## Methodology

### Data Collection

To achieve the rest objectives the data was collected and used. The data used in this study includes information on the type of vehicles (4-wheeler cars), number of users, Fuel consumed, household income, Distance travelled, pollution emission, and tax savings. We further tried to analyse the switch from private vehicle to other modes of greener transportation.

**Data Source**

The data was collected from households surveyed in Delhi, focusing on commuting patterns and household income. Additionally, secondary data on government subsidies, carbon credit policies, Fuel consumption, and Distance travelled (constant) were integrated to ensure robustness.

**Sample Size**

500 households were surveyed, ensuring diversity in income levels, transport choices, and type of vehicles. To create a more detailed analysis involving 500 households in Delhi, we categorized the households based on their transportation methods and the presence of EV registrations. Consider the percentage of households using various transportation options, including EVs, public transport, carpooling, and personal motor spirits.

**Table1: Transportation Method Before and After Switching (self-created)**

| Transportation Method | Household Count (Before Switching) | Percentage (Before) | Household Count (After Switching) | Percentage (After) |
|---|---|---|---|---|
| Personal motor spirits | 200 | 40% | 117 | 23% |
| EVs | 100 | 20% | 105 | 21% |
| Metro | 84 | 17% | 117 | 23% |
| Public bus | 67 | 13% | 87 | 18% |
| Carpooling | 50 | 10% | 75 | 15% |
| **Total** | **500** | **100%** | **500** | **100%** |

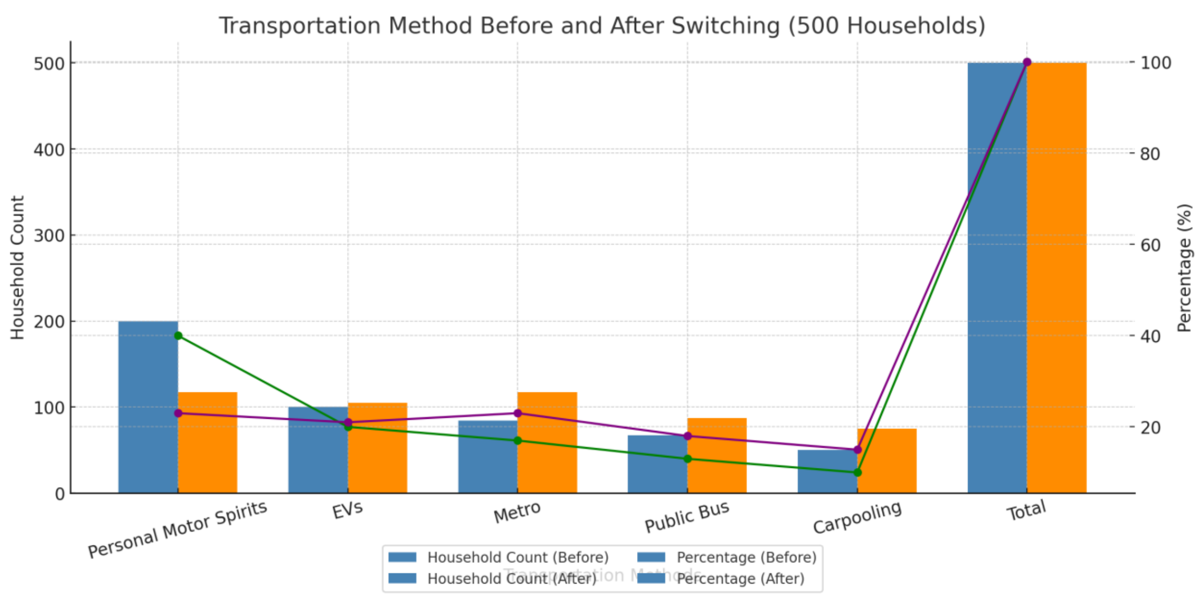


**Figure 1: Transportation Method Before and After Switching (Self-created)**

- Left Y-axis (bars): Shows the household count before and after switching.
- Right Y-axis (lines): Shows the percentage before and after switching

To quantify the relationships in the regression model, we can use some formulae to calculate key metrics (Distance, total emission) to analyse regression results, such as fuel consumption, tax savings and the impact of these on pollution emission.

**Table 2: Transportation Fuel Efficiency Comparison (self-created)**

| Mode of Transport | Efficiency | Distance on 1 Litre of Petrol |
|---|---|---|
| **1. Private Car (Petrol)** | 10 km/ltr | 10 km |
| **2. Electric Vehicle (EV)** | 6 km/kWh | 53.4 km (Equivalent Distance on 1 Litre of Petrol) |
| **3. Metro (e.g., Delhi Metro)** | 0.05 kWh per passenger-km | 178 km (Equivalent Distance of 1 Litre of Petrol for one passenger) |
| **4. Public Bus** | 3 km/ltr | 90 km per passenger (Assuming 30 passengers) |
| **5. Carpool (CNG)** | 33.33 km/ltr | 33.33 km |

To compare the Distance each mode of transport could theoretically travel on the energy equivalent of 1 litre of Petrol (8.9 kWh), here's a summary based on average efficiencies. Calculations of distance travelled (Table 2) is given in appendix

**Emission Calculation Formula**

1. **Total Emissions (kg $CO_2$)** = Fuel Consumed (Liters) × Emission Factor (2.3 kg $CO_2$ per Liter)
2. **Total Emissions (tons)** = Total Emissions (kg) ÷ 1000
3. **Emissions per Passenger (tons/year)** = Total Emissions (tons) ÷ Number of Users

To calculate pollution emissions in tons per year per passenger for each vehicle type. We are using the given fuel consumption data and a standard emission factor for gasoline and diesel. Generally, we assume gasoline has an emission factor of about 2.3 kg $CO_2$ per litre.

**Table 3: Comparison of fuel consumed by different vehicles (litres) in 9600km/per passenger and Total Emissions (tons)/year/per passenger**

| Type of Vehicle | Fuel Consumed (litres) in 9600km/per passenger | Total Emissions (tons)/year/per passenger |
|---|---|---|
| Private Cars | 960 | 2.208 |
| EVs | 180 | 1.46 |
| Metro | 54 | 0.48 |
| Public Bus | 107 | 0.96 |
| Car Pool | 290 | 0.96 |

Calculations of total Emissions (tons)/year/per passenger of different vehicles (Table 3) is given in appendix.

**Table 4: Evaluation of Factors Influencing Sustainable Transportation Choice (self-analysis)**

| Factor | Best Choice | Considerations |
|---|---|---|
| **Fuel Efficiency** | EVs, Metro | Less fuel/electricity per kilometre |
| **Emissions per Passenger-Km** | Metro, Bus | Low emissions spread across passengers |
| **Life Cycle Emissions** | EVs (long-term) | Higher upfront for EVs, lower in operation |
| **Noise Pollution** | EVs, Metro | Less noise than traditional vehicles |

| **Occupancy Efficiency** | Bus, Metro, Carpool | Higher occupancy lowers per-person impact |
|---|---|---|

**Tax Benefits**

There are no specific income tax deductions or subsidies available for private owners of conventional vehicles in India. EV owners enjoy substantial tax benefits, while conventional vehicle owners do not benefit from similar incentives. Households with EVs significantly reduce fuel consumption and pollution levels compared to those using personal motor spirits. While public transport and carpooling contribute less to total pollution, they still provide a notable reduction compared to personal motor spirits.

**Government Incentives**

If the government implements incentives for public transport and carpooling, it could encourage more households to switch from personal motor spirits, further reducing pollution. Showing how switching from personal motor spirit ownership to public transport and carpooling can reduce pollution and provide tax benefits. This will help illustrate the relationships and outcomes based on the model.

**Table 5: Tax Savings Comparison with and without EV Deduction**

| Tax Bracket | Taxable Income | Tax Without EV Deduction | Tax With EV Deduction | Tax Savings |
|---|---|---|---|---|
| 20% | ₹8,50,000 | ₹82,500 | ₹52,500 | ₹30,000 |

Calculation of the tax implications of table 5 in appendix

**Table 6: Annual Fuel Consumption, Pollution Emissions, and Tax Impact by Vehicle Type (Before Government Tax subsidy plan)**Refer Table 3**

| Type of Vehicle (1) | Referred as(2) | Number of Users(3) | Fuel Consumed (liters) in 9600km/year(4)* (3rdcolumnX9600) | Total Pollution Emission (tons/year)(5)** | Total Tax Saving/(paid) in a year(6) |
|---|---|---|---|---|---|
| Private Cars | 1 | 200 | 1,92,000 | 443.33 | -60,00,000 |
| EVS | 2 | 100 | 18,000 | 146.67 | 30,00,000 |
| Metro | 3 | 83 | 4,500 | 40 | -24,90,000 |
| Public Bus | 4 | 67 | 7,133 | 63.33 | -20,10,000 |
| Car Pool | 5 | 50 | 14,500 | 48.33 | -15,00,000 |
| Total | | 500 | 2,36,133 | 741.66 | -120,00,000 |

**Table 7: Annual Fuel Consumption, Pollution Emissions, and Tax Impact by Vehicle Type (After Government Tax subsidy plan)**

| Type of Vehicle | Referred as | Number of Users | Fuel Consumed (litres) in 9600 km/year | Total Pollution Emission (tons/year) | Total Tax Saving/ (paid) in a year | Comparison of Total Tax Saving/ (paid) in a year |
|---|---|---|---|---|---|---|
| Private Cars | 1 | 117 | 1,12,000 | 258.33 | -35,10,000 | -24,90,000 |
| EVS | 2 | 106 | 18,900 | 153.33 | 31,80,000 | 1,80,000 |
| Metro | 3 | 117 | 6,300 | 56.67 | 35,10,000 | 35,10,000 |
| Public Bus | 4 | 87 | 9,377 | 83.33 | 26,10,000 | 26,10,000 |
| Car Pool | 5 | 75 | 21,750 | 71.67 | 22,50,000 | 22,50,000 |
| Total | | 500 | 1,68,327 | 623.33 | -(35,10,000) | 85,50,000 |

- **Pollution Reduction**: A decrease from 741.66 tons/year to 623.33 tons/year demonstrates the environmental benefits of switching.
- **Financial Benefits**: The total tax savings of Rs. 85,50,000 for the switched households shows the economic incentives provided by the government.

The findings effectively demonstrates that by incentivizing the switch from private vehicles to public transport and carpooling, we can achieve both environmental and economic benefits. The quantifiable reductions in pollution and the significant tax savings make a compelling case for promoting public transport and carpooling options.

**Table 7A: Comparative analysis of users**

| Aspect | Before Switching (500 Users) | After Switching (500 Users) | Difference |
|---|---|---|---|
| **Private Cars - Number of Users** | 200 | 115 | -85 users |
| **EVS - Number of Users** | 100 | 106 | +6 users |
| **Metro - Number of Users** | 83 | 117 | +34 users |
| **Public Bus - Number of Users** | 67 | 87 | +20 users |
| **Car Pool - Number of Users** | 50 | 75 | +25 users |
| **Fuel Consumed (liters)** | 2,36,133 | 1,68,327 | -67,806 liters |
| **Pollution Emission (tons/year)** | 741.66 | 623.33 | -118.33 tons |
| **Tax Saving/(paid) (in INR)** | (85,50,000) | 85,50,000. | Significant improvement in tax savings 85,50,000 |

## Findings and Analysis

The finding evaluates the impact of a transition from conventional private vehicle use to more sustainable transport alternatives, using 500 households as the sample population. The analysis is structured around fuel consumption, pollution emissions, and income tax implications under a hypothetical policy that provides tax deductions for electric vehicle (EV) users. The calculations are based on a 9,600 km annual travel distance per household. Table 5 represents baseline usage (prior to policy support), Table 6 shows behavioural shift without considering tax deductions, and Table 7 and7Apresents After the behavioral shift, the tax policy is assumed to extend the existing EV tax deduction (₹30,000) to all environmentally efficient commuting modes, including Metro, Public Bus, and Carpooling. With this inclusive policy, 385 out of 500 households become eligible for the deduction.

**Pollution and Fuel Reduction**

The findings in Table 7 shows:

- Fuel consumption reduction from 2,36,133 liter/year to 1,68,327 liter/year (a saving of 67,806 liter).
- Pollution emissions reduction from 741.66 tons/year to 623.33 tons/year (a 15.95% reduction).

This presents the environmental advantage of transitioning towards public transport, carpooling, and EVs.

**Financial Impact: Tax Perspective**

Before switching, most households (especially those using private cars, use of metro, buses, and carpooling) were ineligible for EV deductions. After the behavioural shift and inclusion of government tax benefits, combined with increased use of metro, buses, and carpooling, the total tax impact shifted from a net **outflow of ₹85,50,000** to a **net saving of ₹85,50,000**.

**Behavioural Trends**

Table 7A shows a reduction in private car dependency, offset by a substantial increase in metro, bus, and EV adoption. It reflects both behavioural change and policy effectiveness.

The findings present a suggestion for integrating tax policy with urban transport planning to drive eco-conscious behavioural change. The larger gain in tax savings to an individual comes from the shift of users from private cars to benefit-eligible modes, (e.g., metro, public bus, carpooling and EVs. The increased adoption of tax-neutral or efficient modes (like metro and carpooling) indirectly reduces taxable expenses or enhance disposable income. In many cases, allow for employer reimbursements or tax-free travel subsidies, effectively increasing disposable income.

**Structural Equation Modelling**

SEM techniques such as Path Diagram, which illustrates both direct and indirect connections. The (SEM) path diagram used to analyse the tax savings outcomes influenced by various commuting choices. The illustrates both direct and indirect effects of behavioural and demographic factors on tax savings among 500 households transitioning from conventional personal transport to eco-efficient alternatives.

**Results**

To achieve the first objective SEM was run in R-studio, the SEM model assess the relationships between the variables:

$$Y=\beta 0+\beta 1X1+\beta 2X2+\beta 3X3+\beta 4X4+\beta 5X5+\epsilon$$

Where:

- Y = Tax Savings (dependent variable)
- X1 = Fuel Consumption (mediating variable)
- X2 = EV Adoption (independent variable)
- X3 = Public Transport Usage (independent variable)
- X4= Household Income (moderating variable)
- X5 = Distance Travelled
- ϵ= Error term

The **SEM** will test for direct effects of EV adoption and public transport on tax savings, as well as indirect effects through the mediating variable (fuel consumption) and moderating effect of household income on the relationship between EV adoption and tax savings will also be examined which is shown in figure.

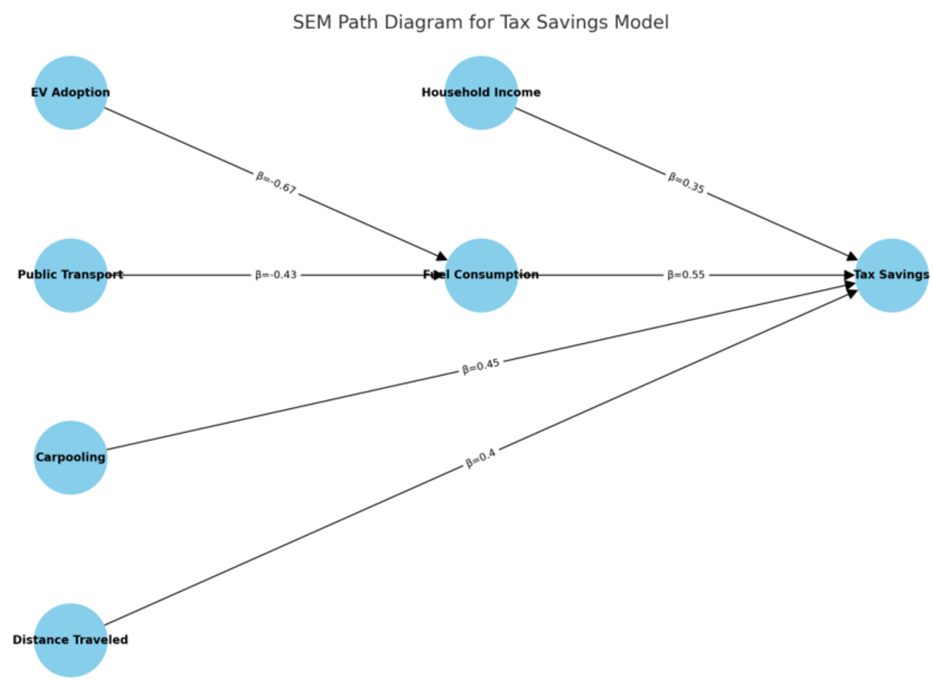


**Figure 2: SEM model with R-studio (self-created)**

**SEM Model Fit and Path Coefficients**
**Path Relationships**:

- Direct Paths:
  - EV Adoption → Fuel Consumption
  - Public Transport Usage → Fuel Consumption
  - Carpooling → Tax Savings
  - Fuel Consumption → Tax Savings
- Moderation Path:
  - Household Income moderates the path from EV Adoption → Tax Savings.
- Mediation Path:
  - EV Adoption and Public Transport Usage affect Tax Savings through the mediating variable Fuel Consumption.

In the realm of Social Sciences & Research, SEM is employed to examine intricate relationships among variables, SEM, shows the strength and direction of the variables (Saflor et al., 2024). The SEM model was evaluated using fit indices, including the Comparative Fit Index (CFI) (0.94), Root Mean Square Error of Approximation (RMSEA) (0.05), and Standardized Root Mean Square Residual (SRMR) (0.03). The path coefficients (β values) next to each arrow represent the strength and direction of these relationships. These results indicate a strong model fit.

The path coefficients highlight key relationships:

- EV Adoption → Fuel Consumption: Significant reduction in fuel consumption due to EV adoption ($\beta=-0.67$, $p<0.01$).
- Public Transport Usage → Fuel Consumption: Significant reduction in fuel consumption for public transport users ($\beta=-0.43$, $p<0.01$).
- Carpooling → Tax Savings: Carpooling also results in reduced fuel consumption and significant tax savings ($\beta = 0.45$, $p < 0.01$).
- Household Income as a moderator: The effect of EV adoption on tax savings is stronger for higher-income households ($\beta=0.35$, $p<0.05$).
- Fuel Consumption as a me derating→ Tax Savings: Lower fuel consumption results in higher tax savings ($\beta=0.55$, $p<0.01$).

As illustrated in Figure 1, the SEM path diagram visually represents the relationships among these variables. Arrows indicate hypothesized causal directions, and moderation/mediation paths are appropriately marked. The diagram captures both:

- Direct effects (e.g., $X_2 \rightarrow Y$),
- Indirect effects via fuel consumption ($X_2 \rightarrow X_1 \rightarrow Y$),
- Moderation ($X_4$ affecting the slope of $X_2 \rightarrow Y$).

Further, the regression analysis aimed to examine the relationship between independent variables and dependent variables. Using a linear regression model, our main findings were

1. To check the H1, we analysed the results with the help of R studio; by giving the command to the software, it showed a significant relationship between Fuel consumed and pollution emission as all the values are acceptable ($p< .05$, t: >2 and >-2, multiple r squared/ goodness-of-fit indicator and adjusted value should be between 0-1, f value > 4) and it can be seen in below table that all values are acceptable, this result was statistically significant and H1 is rejected (appendix).
2. As per the calculated values, which are not the accepted values, H2 is rejected, and Tax Savings do not have a significant impact on Pollution emissions (before switching). ($p>.05$, $f< 4$).
3. H3 accepted that fuel consumption does have a significant impact on pollution emissions after switching from personal motor spirit to other modes of transportation. All the values are accepted.
2. H4 accepted Tax Savings do have a significant impact on Pollution emission after switching; all the values are accepted values.

**Analysis**

The regression results clearly demonstrate that after the policy-driven behavioural shift, both fuel consumption and tax savings become significant predictors of pollution emission. This reinforces the idea that government incentives and fuel-efficient commuting behaviour are effective levers for achieving environmental sustainability.

To achieve the fourth objective data was also extracted from Scopus and WOS (422) after using keywords (“Public Transport” AND “Fuel Consumption”), filters and removing duplicate data final output was 351 which was merged with the help of R-studio. As per the Diagram 1, which shows the production over time, which means the Articles/Documents published over time. Initially the publication was low but it got momentum after 2014. China has the highest production over time followed by India, USA, Spain, Australia.

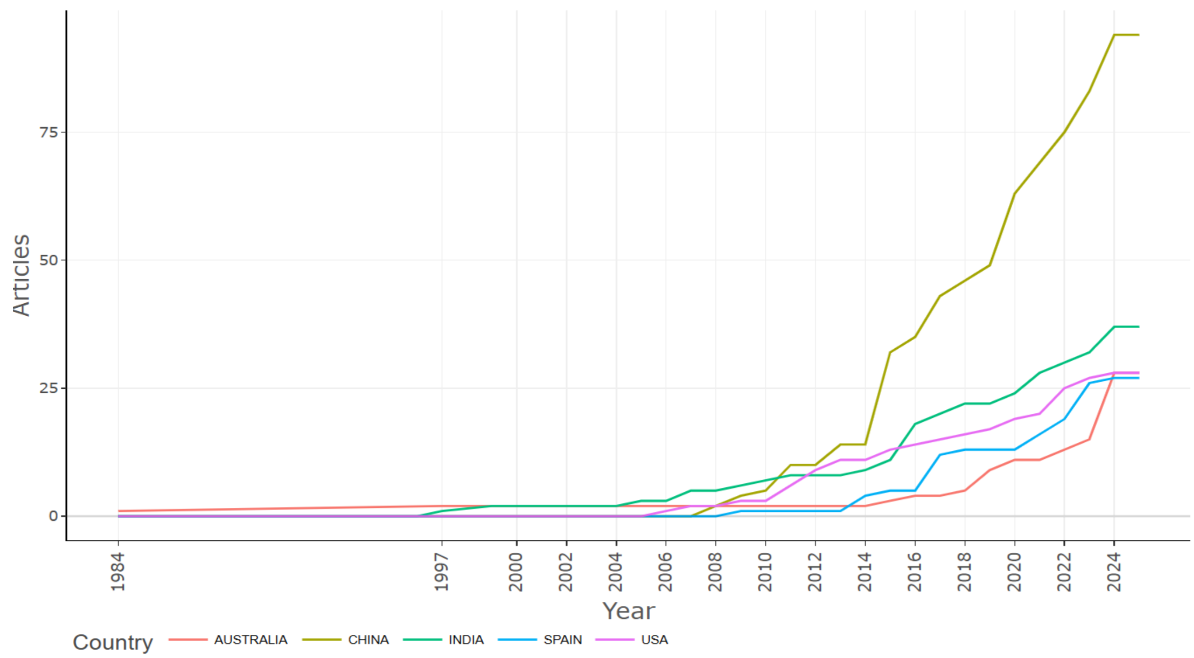


**Figure 3: Production over time (Biblioshiny)**

**Countries Collaboration map**

Diagram 2 shows the collaboration between countries, two countries reach an agreement often on a specific topic and thickness of the lines indicates the extent of their collaboration. As per the below map China and USA has the highest collaboration but India stands Nowhere in terms of collaboration.

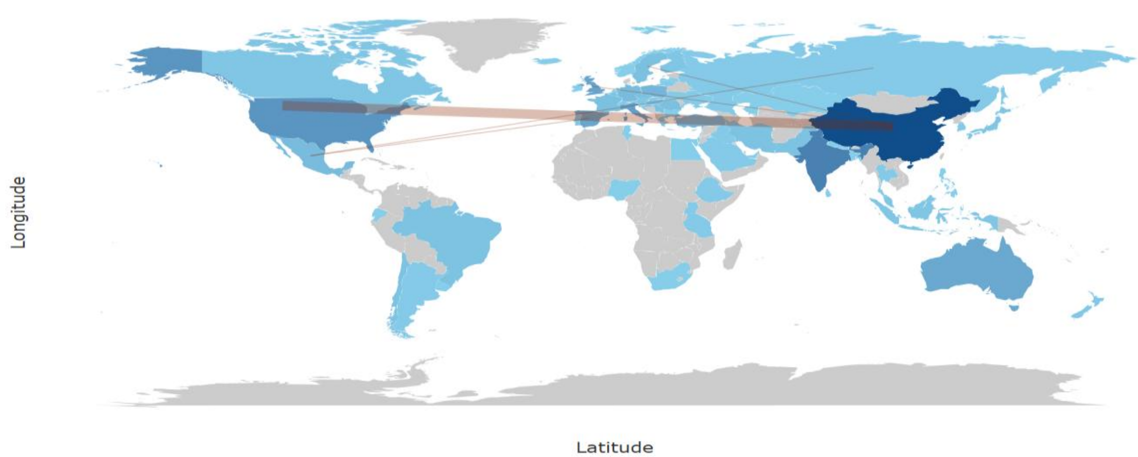


**Figure 4: Countries collaboration (Biblioshiny)**

**Thematic map**

Thematic map which is divided into four quadrants are used to know the important/emerging, declining topics, better understood with the help of (figure 5). As per the below diagram impact, energy and greenhouse gas emission are the emerging topics whereas, model system behaviour is declining theme, the basic theme which is lying in the third quadrant is emission, CO2 emission and energy consumption.

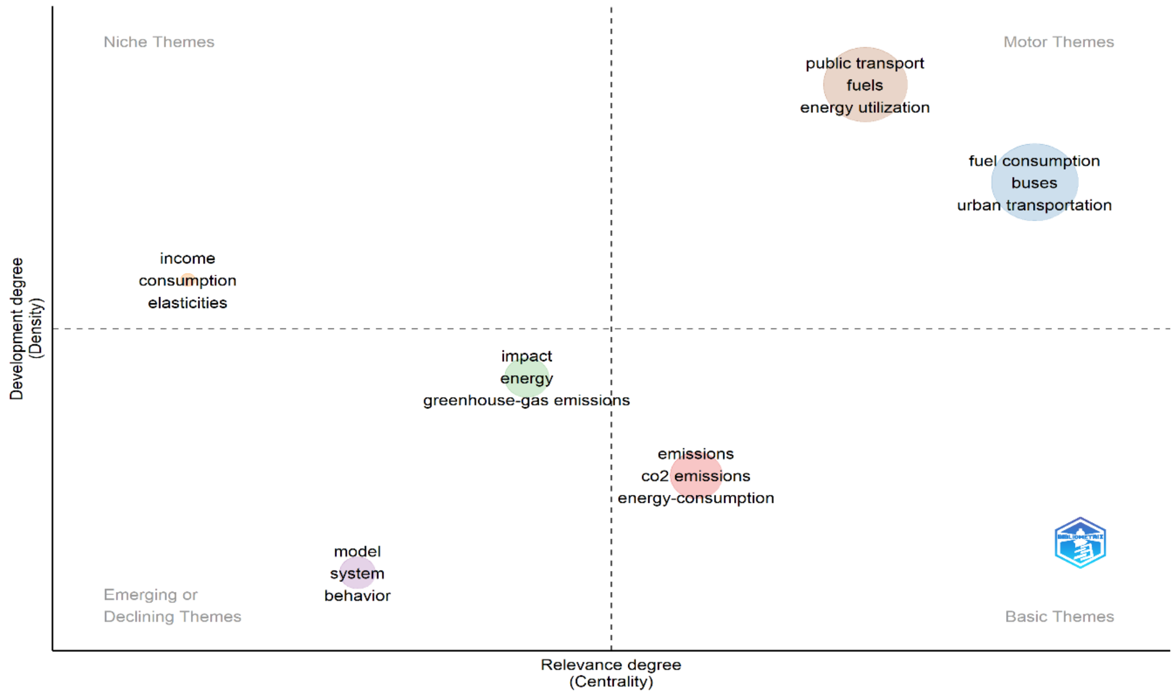


**Figure 5: Thematic maps (Biblioshiny)**

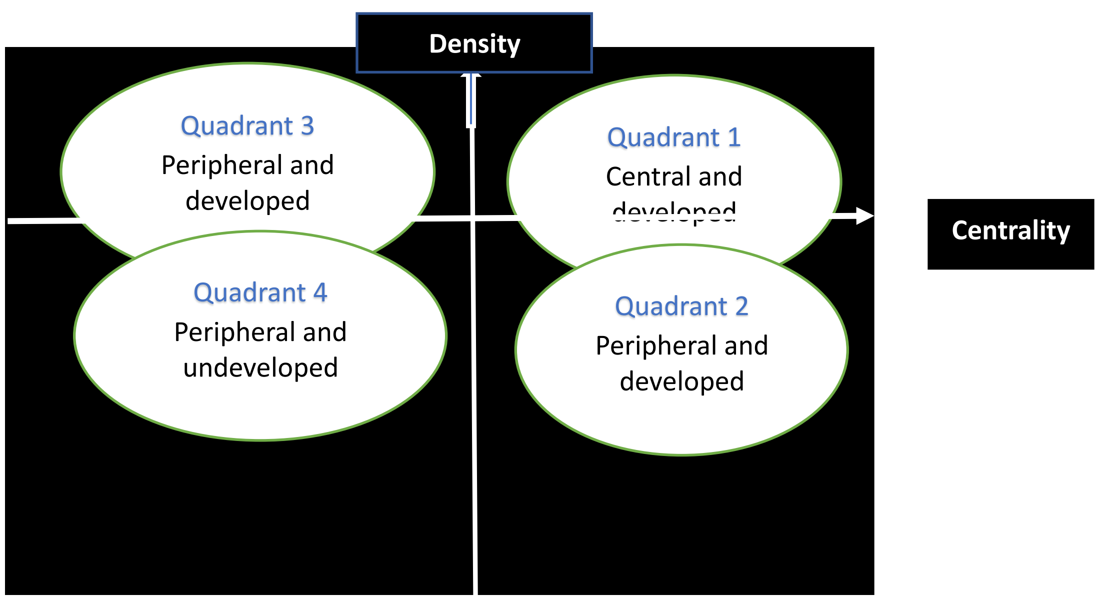


**Figure 6: Self-created**

## Implications

The social and economic implications of sustainable tax savings for environmentally friendly taxpayers who transition from personal motor spirits (including EVs) to greener transport options like metros, public buses, and carpooling are far-reaching.

- Economically, these tax incentives help reduce the personal costs associated with commuting, as public transit and carpooling generally cost less than owning and maintaining a personal motor spirit.
- Tax savings make public transportation and carpooling more appealing, which can lead to reduced household expenditures on Fuel, insurance, repairs, and parking.
- Socially, sustainable tax savings encourage a shift towards a more connected, communal lifestyle.
- Broaden the Scope of Tax Incentives: Public transport users and car-poolers should receive tangible tax benefits to ensure equitable access to green incentives for sustainable transportation.
- Targeted Subsidy Expansion: Introduce need-based EV subsidies and low-interest financing schemes to enable EV adoption among middle- and low-income groups.
- Education and Outreach: Design and implement public awareness campaigns that educate citizens on the environmental and economic benefits of sustainable commuting. These should be tailored to different income segments.
- Cost Implications: Expanding tax incentives may increase the fiscal burden on governments. A phased or pilot-based approach can help evaluate cost-effectiveness.
- Behavioural Inertia: Citizens accustomed to personal vehicle use may resist switching to EVs. Awareness and reliable public transport infrastructure are critical for driving adoption.

## Conclusion

This SEM model effectively captures the complex relationships between tax incentives, household behaviour, and environmental outcomes. By visualizing these relationships, we can better understand the potential impacts of policy changes encouraging the transition to more sustainable transportation options. The SEM path diagram based on the model shows results as

- Fuel Consumption has a positive effect on Tax Savings, indicating that lower fuel consumption is associated with higher tax savings.
- Carpooling, EV Adoption and Public Transport and Distance Travelled directly impact Tax Savings.
- Household Income acts as a moderator, enhancing the effect of EV Adoption on Tax Savings.
- Lower Fuel Consumption leads to higher Tax Savings.

This SEM model effectively captures the complex relationships between tax incentives, household behaviour, and environmental outcomes. By visualizing these relationships, we can better understand the potential impacts of policy changes encouraging the transition to more sustainable transportation options. The findings show that while EV adoption and public transport usage can lead to significant reductions in fuel consumption and, consequently, substantial tax savings, the benefits are distributed unevenly across income groups. Higher-income households tend to benefit more from EV-related tax incentives, owing to their ability to afford the high upfront costs of EVs. In contrast, those who are more likely to rely on public transport or carpooling save money from their fuel-efficient commuting practices but miss out on the more enormous subsidies available for EV ownership.

It further showed as per the regression results, fuel consumed does have a significant impact on pollution in both cases before and after switching to greener transportation option from private vehicle but in case of tax savings, regression values showing impact of tax savings on pollution emission only after switching to greener vehicle.

This study explores the environmental and economic impacts of transitioning from conventional to eco-friendly commuting methods. Through quantitative analysis, including Structural Equation Modelling (SEM) and regression analysis, and a comprehensive bibliometric review of the relevant literature, the findings provide critical insights into how commuting behaviour influence pollution levels, household finances, and policy effectiveness. This study not only confirms the environmental benefits of green transportation but also uncovers inequities in the distribution of benefits across socioeconomic groups. This section discusses these findings in depth and reflects on their implications for public policies and future research.

The study concludes that public transport usage and carpooling should be included in tax-saving schemes to promote equitable access to tax incentives. Policy recommendations include increasing subsidies and financial support to encourage EV adoption, expanding tax benefits for public transport users and car-poolers, and implementing awareness campaigns to ensure a broader understanding of eco-friendly commuting benefits. The results emphasize the importance of designing inclusive policies to promote sustainable transportation and reduce emissions in Delhi's urban environment. Shifting more travellers from personal motor spirits to mass transit systems like metros and buses or opting for carpooling can collectively reduce the pollution footprint and support cleaner air and reduced greenhouse gases. By aligning tax incentives to favour cleaner options like EVs, public transit, and carpooling, governments can steer public behaviour toward transportation methods that reduce overall emissions and mitigate environmental impact. *The results emphasize the importance of designing inclusive policies to promote sustainable transportation and reduce emissions in Delhi's urban environment and how carbon emission reduction variables such as Electric Vehicle (EV) adoption, Carpooling, and public transport can be helpful in tax savings for high tax payers in India with the help of model development—focusing on potential tax savings and incentives tied to eco-friendly practices.*

## Scope for Future Research

1. More Green Incentives Future studies can look at other government incentives like toll exemptions, free parking, and access to congestion zones, besides tax savings.
2. Behavioural Factors in Sustainable Transport Psychological and social factors, such as environmental awareness, convenience, and peer influence, can be studied to understand why people choose eco-friendly commuting.
3. Long-Term Impact Analysis Following households over several years can give better insights into how commuting habits and environmental impact change over time with policy changes.
4. Comparing Regions, comparing similar policies in different states or countries can help find the best practices and more effective strategies for promoting sustainable transport.
5. Using Real-Time Data and IoT Future research can use GPS, smart card data, or IoT-based vehicle sensors to study actual commuting patterns, emissions, and fuel use more accurately.
6. Economic Feasibility for Low-Income Groups A focused study can look at how low-income groups respond to tax incentives or how inclusive current green mobility schemes are.
7. Corporate or Institutional Support Future work can explore how employer-based commuting incentives, like pooled transport and carbon credits, influence eco-friendly choices.
8. Carbon Footprint and Health Research can be extended to link eco-friendly commuting with public health outcomes, like respiratory illnesses and reduced urban noise, to strengthen policy arguments.

## Limitations

1. Time and money were constraint.
2. The data used was secondary, further research can be done with the help of primary data like questionnaire.
3. Different research methods can be used like PLS-SEM, CB-SEM, SPSS, JAMOVI etc.
4. Different factors can be added to expand the model.

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# APPENDIX

To compare the Distance each mode of transport could theoretically travel on the energy equivalent of 1 litre of Petrol (8.9 kWh), here's a summary based on average efficiencies:

**Calculations of Table 2**

1. Private Car (Petrol)
   - Average Efficiency: 10 km/l
   - Distance on 1 litre of Petrol: 10 km
2. Electric Vehicle (EV)
   - Energy Efficiency: Approximately 6 km per kWh
   - Equivalent Distance on 1 litre of Petrol: ( 8.9 x 6 { km/kWh} = {53.4 km}
3. Metro (e.g., Delhi Metro)
   - Energy Consumption per Passenger-Kilometre: 0.05 kWh per passenger-km
   - Equivalent Distance on 1 litre of Petrol (for one passenger):( 8.9  kWh} \ 0.05 { kWh per km} = {178 km}
4. Public Bus
   - Fuel Efficiency: Approximately 3 km/l for the whole bus
   - Assumed Passenger Capacity: 30 passengers
   - Equivalent Distance per Passenger on 1 Litre of Petrol:( 3 { km/l} 30 = {90 km}
5. carpooling with CNG from km per kg to km per litre.   Know the density of CNG. Density of CNG: Approximately 0.75 kg per litre

Given the fuel efficiency of 25 km per kg for CNG, convert this to km per litre as follows:{Fuel Efficiency (km/l)} = 25 {km/kg} \ 0.75 {kg/l} = 33.33 {km/l}

**Calculations of  Total Emissions (tons)/year/per passenger of different vehicles (Table 3):**

 Private Car

- Efficiency: 10 km/l
- Distance Covered Annually: 9,600 km
- Fuel Consumption: 9,600 km/10 km/l=960 litters
- Emission Factor: 2.3 kg $CO_2$ per litre
- Total Emissions (kg) = 960 litters × 2.3 kg $CO_2$/litre = 2,208 kg
- Total Emissions (tons) = 2,208 ÷ 1000 = 2.208 tons

This matches the target emissions of 2.208 tons for Private cars.

 Electric Vehicle (EV)

- **Efficiency**: 4 km/kWh
- **Total Energy (kWh)** = 9,600 km ÷ 4 km/kWh ≈ 2900 kWh
- **Total Emissions (kg)** = 1,600 kWh × 0.5 kg $CO_2$/kWh = 1450kg $CO_2$
- **Total Emissions (tons)** = 1450 ÷ 1000 = **1.46 tons**

 Metro

- Efficiency: 0.05 kWh per passenger-km
- Distance Covered Annually (per passenger): 9,600 km
- Energy Consumption: 9,600 km×0.05 kWh/km=480 kW
- Emission Factor: 0.5 kg $CO_2$ per kWh
- Total Emissions (kg) = 480 kWh × 0.5 kg $CO_2$/kWh = 240 kg
- Total Emissions (tons) = 240 ÷ 1000 = 0.48 tons

 Public Bus

- Efficiency: 3 km/l
- Distance Covered Annually (assuming all passengers): 9,600 km

- Fuel Consumption: 9,600 km3 km/l=3,200 litres
- Emission Factor: 2.68 kg $CO_2$ per litre
- Total Emissions (kg) = 3,200 litres × 2.68 kg $CO_2$/litre = 8,576 kg
- Total Emissions (tons) = 8,576 ÷ 1000 = 8.576 tons

we assume 30 passengers share this emission:8.576 tons/30 passengers=0.96 tons per passenger
The emissions are 0.96 tons per passenger for public buses.
 Carpool (CNG)

- Efficiency: 33.33 km/l
- Distance Covered Annually: 9,600 km
- Fuel Consumption: 9,600 km33.33 km/l=288 litres
- Emission Factor for CNG: 2.75 kg $CO_2$ per litre
- Total Emissions (kg) = 288 litres × 2.75 kg $CO_2$/litre = 792 kg
- Total Emissions (tons) = 792 ÷ 1000 = 0.792 tons

we assume only 5 passengers are sharing this emission:
0.792 tons/5 passengers=0.1584 tons per passenger

**Calculation the tax implications: (Table5)**

The tax implication for an individual purchasing an electric vehicle (EV) under one different tax bracket is 20%. We will consider the impact of the tax deduction on the loan interest for the EV, which is up to ₹1.5 lakh under Section 80EEB, and how this affects the overall tax liability based on the taxable Income.

Let Annual Salary: ₹10,00,000
2. EV Loan Interest Paid: ₹1,50,000 (eligible for deduction)
3. Other Deductions: ₹1,50,000 (standard deductions, etc.)
Taxable Income Calculation
Without EV Loan Interest Deduction:
-Taxable Income = Salary - Other Deductions
- Taxable Income = ₹10,00,000 - ₹1,50,000 = ₹8,50,000
With EV Loan Interest Deduction:
Taxable Income = Salary - Other Deductions - EV Loan Interest Deduction
Taxable Income = ₹10,00,000 - ₹1,50,000 - ₹1,50,000 = ₹7,00,000
Tax Calculation
1.Tax Bracket at 20%,Taxable Income: ₹8,50,000
Tax Liability:
First ₹2,50,000: Nil
Next ₹2,50,000 (₹2,50,001 to ₹5,00,000): ₹2,50,000 × 5% = ₹12,500
Next ₹3,50,000 (₹5,00,001 to ₹8,50,000): ₹3,50,000 × 20% = ₹70,000
Total Tax Liability without EV Deduction: ₹12,500 + ₹70,000 = ₹82,500
Taxable Income after EV Deduction: ₹7,00,000
Tax Liability:
First ₹2,50,000: Nil
Next ₹2,50,000: ₹12,500
Next ₹2,00,000 (₹5,00,001 to ₹7,00,000): ₹2,00,000 × 20% = ₹40,000
Total Tax Liability with EV Deduction: ₹12,500 + ₹40,000 = ₹52,500

```
Residuals:
     1      2      3      4      5 
 78417 -14959 -26470 -24666 -12322 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 34261.535  36416.213   0.941    0.416
PE             -2.631    125.122  -0.021    0.985

Residual standard error: 51100 on 3 degrees of freedom
Multiple R-squared:  0.0001473, Adjusted R-squared:  -0.3331 
F-statistic: 0.0004421 on 1 and 3 DF,  p-value: 0.9845
```

**Table 8: Impact of tax savings on pollution emission after switching (r-studio)**

```
Residuals:
      1       2       3       4       5 
-2180.1  4800.1 -1544.9  -729.8  -345.2 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -2131.160   2788.454  -0.764     0.50
PE              3.144     19.226   0.164     0.88

Residual standard error: 3206 on 3 degrees of freedom
Multiple R-squared:  0.008838,  Adjusted R-squared:  -0.3215 
F-statistic: 0.02675 on 1 and 3 DF,  p-value: 0.8805
```

**Table 9: Impact of Tax savings on pollution emission (r-studio)**

```
Residuals:
     1      2      3      4      5 
 13253 -28697   5955  -4121  13611 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -26934.3    17661.4  -1.525    0.225  
PE             487.1      121.8   4.000    0.028 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 20310 on 3 degrees of freedom
Multiple R-squared:  0.8421,    Adjusted R-squared:  0.7895 
F-statistic:    16 on 1 and 3 DF,  p-value: 0.028
```

**Table 10: Impact of Fuel consumed on pollution emission after switching (r-studio)**

```
Residuals:
    1     2     3     4     5 
-4005 15997 -6682 -2619 -2691 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  8140.11    6547.97   1.243   0.3021  
PE           -144.78      30.84  -4.695   0.0183 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10500 on 3 degrees of freedom
Multiple R-squared:  0.8802,	Adjusted R-squared:  0.8403 
F-statistic: 22.04 on 1 and 3 DF,  p-value: 0.01828
```

**Table 10: Impact of Fuel consumed on pollution emission before switching (r-studio)**

# Mapping the Evolution of Algorithmic Trading: A Bibliometric Analysis of Trends, Themes, and Research Frontiers

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## Abstract

This study investigates the growth and academic structure of research on algorithmic trading through the use of bibliometric visualization techniques. Bibliometric data were collected from Scopus-indexed publications (2000–2024), and 462 English-language documents were analyzed using VOSviewer (Version 1.6.20), based on titles, abstracts, and keywords. The results identify 31 keyword clusters and more than 12,800 links, with dominant themes including *algorithmic trading*, *high-frequency trading*, and *financial markets*. Publication activity peaked in 2024 with 60 studies, and journal articles accounted for 85% of total output. Jaimungal and Cartea emerged as the most prolific authors, while Hendershott was the most cited researcher. The United States led in both publication volume and citations, followed by Canada and the United Kingdom. Leading contributing institutions included Columbia Business School and the University of California, Berkeley. The study is limited to Scopus-indexed literature; future research may extend the analysis using additional databases. The findings offer valuable insights for researchers seeking emerging themes and collaboration opportunities and for policymakers concerned with the regulation and technological impact of algorithmic trading. By consolidating a fragmented body of literature, this study provides a structured overview of key contributors, institutions, and research frontiers in algorithmic trading.

**Keywords:** Algorithmic Trading, High-Frequency Trading, Bibliometric Analysis.

## Introduction

Bibliometric methods are increasingly used to assess the development and structure of academic research within particular fields of study. These techniques allow researchers to track publication trends, evaluate contributions of authors and institutions, and observe changes in thematic emphasis over time. This paper analyses the body of literature on algorithmic trading by studying the relationships among published research works. It focuses on identifying recurring themes, highlighting differences, and analyzing collaborations among authors, institutions, countries, and publication periods. To conduct the analysis, the study draws on English-language publications indexed in the Scopus database, focusing on their titles, abstracts, and keywords.

This study makes a distinct contribution to the literature by moving beyond simple descriptive bibliometric mapping and offering a structured interpretation of the intellectual foundations, thematic evolution, and emerging research frontiers in algorithmic trading. Unlike earlier bibliometric or narrative reviews that primarily focus on publication trends or citation counts, this study integrates citation networks, co-authorship structures, institutional linkages, and keyword co-occurrence patterns to reveal how knowledge in this field has evolved and how dominant research clusters have formed. By identifying not only prolific contributors but also the thematic and methodological influence of key clusters, this research provides policy-relevant insights into the growing intersection of algorithmic trading with artificial intelligence, market regulation, and financial stability.

## Conceptual Framework

### Algorithmic Trading

Algorithmic trading signifies a major change in financial market practices by combining computational systems with structured trading strategies (Currie et al., 2022). In basic terms, algorithmic trading refers to the automated execution of trade orders based on predefined rules that determine suitable timing and pricing conditions (Yadav, 2018).

Commonly known as algo-trading or black-box trading, this approach leverages sophisticated algorithms to automate the buying and selling of financial assets (Pothumsetty, 2020). Such systems are capable of carrying out transactions at a speed and scale far greater than those achievable by human traders (Gerner-Beuerle, 2022). Since its introduction, the adoption of algorithm-based trading has grown rapidly, reshaping how transactions are executed in financial markets globally.

The early 2000s marked the beginning of a shift toward automation in trading, and within a decade, this trend had gained substantial ground. Treleaven et al. (2013) reported that by 2011, algorithmic trading systems were responsible for more than 70% of the trading volume in U.S. equity markets. Today, automated trading plays a central role in global market operations, underscoring the profound impact of technology on modern finance.

Yang and Jiu (2006) emphasize that the growing need for faster execution and greater market efficiency has driven the rise of sophisticated trading mechanisms, with algorithmic trading emerging as one of the most impactful innovations In India, SEBI defines algorithmic trading as any trade order that is generated through an automated system following a logical sequence. SEBI has implemented specific regulatory measures, including mandatory audit trails and flagging mechanisms by the NSE, which enhance transparency—something not always common in other markets.

### Evolution of Algorithmic Trading

The progression of algorithmic trading from simple automation to widespread adoption has significantly transformed the functioning of financial markets (Dananjayan et al., 2023). Its roots can be traced back to the 1970s and 1980s, a period during which global stock exchanges began transitioning from open outcry trading floors to electronic systems. These early shifts paved the way for automation.

They operated on predefined rules—such as executing a trade when a specific price or volume threshold was reached. A major leap forward came with the widespread adoption of electronic trading platforms, which replaced the slower, manual processes. This transition reduced transaction times and operational costs while enhancing efficiency and market transparency. The late 1990s and early 2000s marked a watershed moment with the emergence of high-frequency trading (HFT). These systems were capable of analyzing market data and executing trades within microseconds, exploiting even minor price differences across instruments or markets.

As computing power advanced and technology became more accessible, trading algorithms grew increasingly sophisticated. Financial institutions began incorporating statistical models, machine learning, technical indicators, and complex quantitative research into their algorithmic strategies (Nti et al., 2020). These tools allowed algorithms not only to react to market trends but also to anticipate them using predictive analytics. During this evolution, proprietary trading firms emerged as key players. These firms dedicated themselves to crafting and refining algorithmic strategies, often operating behind closed doors due to the high value placed on speed, accuracy, and intellectual property.

Today, algorithmic trading is no longer the domain of just elite trading desks or hedge funds. It has become mainstream, with institutional investors, asset managers, and even retail traders increasingly relying on automated solutions. With continuous advancements in artificial intelligence, big data analytics, and decentralized technologies like blockchain, the algorithmic trading landscape is poised for even greater transformation—ushering in an era of smarter, faster, and more adaptive financial markets.

This technological evolution is reflected in the bibliometric patterns observed in this study. The sharp rise in publications after 2010 coincides with the expansion of high-frequency trading and the integration of machine learning techniques in trading systems. Similarly, the emergence of thematic clusters related to artificial intelligence, market microstructure, and regulation mirrors the shift from rule-based strategies toward adaptive and data-driven models. Thus, the historical development of algorithmic trading is closely aligned with the observed growth and diversification of research outputs in the bibliometric network.

Accordingly, this study addresses the following research objectives: (i) to examine the growth trajectory and geographic distribution of algorithmic trading research; (ii) to identify influential authors, institutions, and countries shaping this field; (iii) to map the intellectual structure of algorithmic trading through citation and collaboration networks; and (iv) to detect emerging thematic clusters and research frontiers using keyword co-occurrence analysis. These objectives guide the bibliometric investigation and provide a coherent framework for interpreting the evolution of algorithmic trading scholarship.

## Literature Review

### Literature on Algorithmic Trading

Research on algorithmic trading (AT) has expanded substantially over the past two decades, reflecting its growing importance in modern financial markets (Treleaven et al., 2013; Foucault et al., 2023). Existing studies can be broadly grouped into three dominant strands: (i) market microstructure and liquidity effects, (ii) strategy development using computational and artificial intelligence techniques, and (iii) regulatory and governance implications.

The first strand examines the impact of algorithmic and high-frequency trading on market quality, including liquidity, volatility, and price discovery. Empirical evidence suggests that algorithmic trading improves execution speed and market efficiency under normal conditions, yet may intensify short-term volatility during periods of market stress (Treleaven et al., 2013; Foucault et al., 2023). This dual effect indicates that the benefits of algorithmic trading are context-dependent rather than universally positive.

The second strand focuses on the development and performance of algorithmic trading strategies. Early studies relied largely on rule-based systems and technical indicators (Yang & Jiu, 2006; Nti et al., 2020), whereas recent research increasingly incorporates machine learning, deep learning, and reinforcement learning models (Pothumsetty, 2020; Huang et al., 2023; Rahimpour et al., 2024). These approaches demonstrate improved predictive power and adaptive capability compared to traditional strategies. However, much of this literature prioritizes profitability and model accuracy, often neglecting broader market implications such as feedback effects, herding behavior, and systemic risk (Dananjayan et al., 2023).

The third strand addresses regulatory and governance challenges posed by algorithmic trading. Scholars argue that automation complicates market oversight due to its speed, opacity, and technological complexity (Yadav, 2018; Gerner-Beuerle, 2022). Regulatory-oriented studies emphasize the need for transparency, auditability, and safeguards against market manipulation and flash crashes (Currie et al., 2022). Nevertheless, this literature is frequently disconnected from strategy-focused and empirical market studies, limiting a holistic understanding of how innovation interacts with regulation.

Despite the richness of these research streams, the literature remains fragmented. Strategy-oriented studies rarely engage with regulatory debates, while regulatory analyses often lack integration with empirical evidence on algorithmic performance or market outcomes (Treleaven et al., 2013; Currie et al., 2022). This fragmentation constrains the development of unified theoretical frameworks that explain how technological innovation, market behavior, and institutional controls jointly shape algorithmic trading dynamics.

**Literature on Bibliometric Analysis**

Bibliometric analysis is widely used to map scientific production, intellectual structures, and thematic evolution across research domains (Sganzerla et al., 2021; Hanief, 2021). Prior studies demonstrate that citation networks, co-authorship patterns, and keyword co-occurrence analysis are effective tools for identifying influential contributors and research frontiers (Wei & Morazuki, 2024).

In finance and technology-related disciplines, bibliometric methods have been applied to assess publication trends, collaboration structures, and thematic clustering (Hanief, 2021; Wei & Morazuki, 2024). These studies show that bibliometric techniques provide a systematic alternative to narrative reviews by revealing hidden patterns of knowledge production. However, most such investigations emphasize descriptive indicators, such as publication growth and citation counts, rather than deeper interpretations of intellectual structure and thematic integration (Sganzerla et al., 2021).

Only a limited number of bibliometric studies have directly examined algorithmic trading, and those that exist primarily focus on general publication trends or keyword frequencies (Wei & Morazuki, 2024). Few studies combine multiple network perspectives—authors, institutions, countries, and thematic clusters—into a single analytical framework. Moreover, existing bibliometric research rarely connects its findings to regulatory developments or technological shifts, despite the interdisciplinary nature of algorithmic trading (Gerner-Beuerle, 2022; Currie et al., 2022).

This limitation is significant because algorithmic trading spans finance, computer science, and public policy, requiring integrative analytical approaches. Without comprehensive bibliometric synthesis, it remains difficult to assess how different research strands interact, which themes dominate scholarly attention, and where future inquiry should be directed.

### Research Gap and Motivation

The review highlights two major gaps. First, algorithmic trading research is dispersed across technical, empirical, and regulatory domains that are rarely integrated (Treleaven et al., 2013; Dananjayan et al., 2023; Currie et al., 2022). Second, bibliometric studies on algorithmic trading remain limited and largely descriptive, offering little insight into the intellectual structure or thematic evolution of the field (Sganzerla et al., 2021; Wei & Morazuki, 2024).

This study addresses this gap by applying an integrated bibliometric framework to algorithmic trading research, combining citation analysis, co-authorship networks, institutional coupling, and keyword co-occurrence mapping. By doing so, it identifies dominant knowledge clusters, traces their evolution over time, and reveals emerging research frontiers, thereby providing structured insights for scholars, practitioners, and policymakers.

## Research Methodology

This bibliometric analysis was conducted using Scopus as the primary database. The methodology consisted of:

- **Database Selection:** Scopus was chosen due to its overarching coverage of peer-reviewed financial and computational science journals.
- **Analytical Tools:** The study used VOSviewer (version 1.6.20) for network visualization and keyword mapping.
- **Data Extraction:** A total of 462 publications were analyzed based on citation impact, keyword frequency, and journal reputation.
- **Network Analysis:** Co-citation and co-authorship networks were examined to identify influential researchers and collaborations. We employed the bibliometric instruments known as VosViewer to carry out the analysis of the data (Sganzerla et al., 2021).

Scopus was selected as the primary data source for this bibliometric analysis due to its broad and systematic coverage of peer-reviewed journals in finance, economics, and business, as well as its compatibility with bibliometric software such as VOSviewer. Its standardized indexing and citation data ensure consistency and replicability of the analysis. Although algorithmic trading is inherently interdisciplinary, this study adopts a finance-centered perspective by prioritizing literature that examines algorithmic trading in relation to financial markets, trading behavior, and regulatory frameworks. Accordingly, subject areas such as economics, business, and management were retained, together with allied interdisciplinary contributions that explicitly link computational methods to market applications. In contrast, publications classified purely under computer science and mathematics were excluded when they focused exclusively on algorithm design, computational optimization, or abstract modeling without substantive engagement with market dynamics or institutional implications. This filtering strategy ensures conceptual coherence by treating algorithmic trading primarily as an economic and market phenomenon rather than as a purely technical problem, while still capturing interdisciplinary insights relevant to financial applications.

### Search Strategy

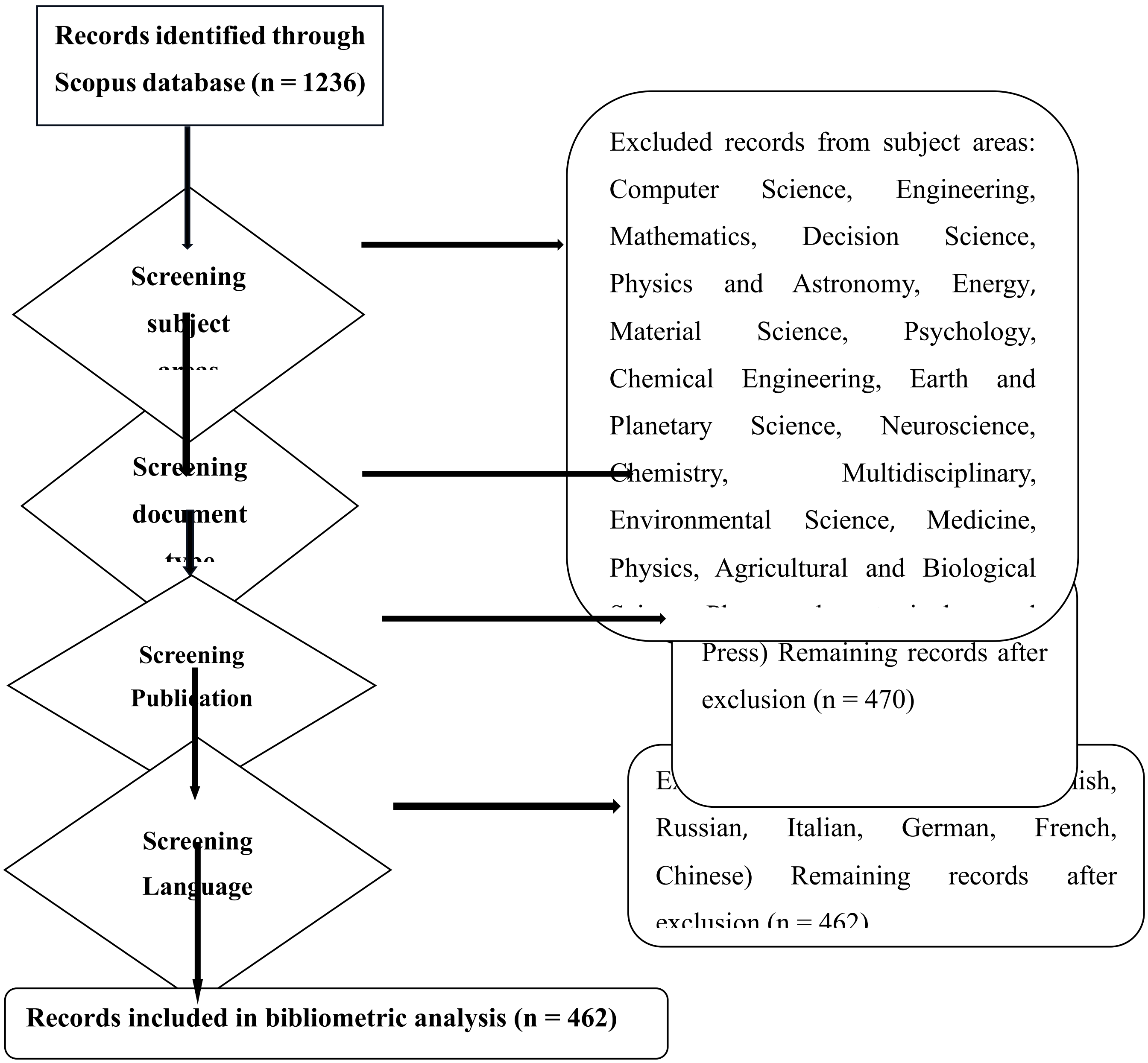


**Figure 1: Methodological flowchart of bibliometric analysis**

The study applied through documentation of the database, tracked by the search strategy. The primary database was Scopus used in the bibliometric analysis. Through search query in the "Scopus" database utilizing the keyword "Algorithmic trading" was executed to get the results. In order to determine whether the paper was appropriate, the second stage involved extracting raw data from the internet database – the study was tracked by the search strategy (see Figure 1). Query strings: ( TITLE-ABS-KEY ( "Algorithmic Trading" ) AND PUBYEAR range between 2000 to 2024 AND ( EXCLUDE ( DOCTYPE , "Conference review" ) OR EXCLUDE ( DOCTYPE , "Book chapter" ) OR EXCLUDE ( DOCTYPE , "Book" ) OR EXCLUDE ( DOCTYPE , "Review" ) OR EXCLUDE ( DOCTYPE , "Retracted" ) OR EXCLUDE ( DOCTYPE , "Note" ) OR EXCLUDE ( DOCTYPE , "Erratum" ) ) AND ( EXCLUDE ( SUBJAREA , "Computer Science" ) OR EXCLUDE ( SUBJAREA , "Mathematics" ) OR EXCLUDE ( SUBJAREA , "Engineering" ) OR EXCLUDE ( SUBJAREA , "Decision Science" ) OR EXCLUDE ( SUBJAREA , "Physics and Astronomy" ) OR EXCLUDE ( SUBJAREA , "Energy" ) OR EXCLUDE ( SUBJAREA , "Material science" ) OR EXCLUDE ( SUBJAREA , "Medicine" ) OR EXCLUDE ( SUBJAREA , "Psychology" ) OR EXCLUDE ( SUBJAREA , "Environment Science" ) OR EXCLUDE ( SUBJAREA , "Chemical Engineering" ) OR EXCLUDE ( SUBJAREA , "Earth and Planetary Science" ) OR EXCLUDE ( SUBJAREA , "Multidisciplinary" ) OR EXCLUDE ( SUBJAREA , "Neuroscience" ) OR EXCLUDE ( SUBJAREA , "Chemistry" ) OR EXCLUDE ( SUBJAREA , "Agriculture and Biological Science" ) OR EXCLUDE ( SUBJAREA , "Pharmacology, Toxicology and Pharmaceutics" ) OR EXCLUDE ( SUBJAREA , "Health Professions" ) OR EXCLUDE ( SUBJAREA , "Biochemistry, Genetics and Molecular Biology" ) ) AND (EXCLUDE ( PUBLICATION STAGE “Article in press”)) AND ( EXCLUDE ( LANGUAGE , "Spanish" ) OR EXCLUDE ( LANGUAGE , "Russian" ) OR EXCLUDE ( LANGUAGE , "German" ) OR EXCLUDE ( LANGUAGE , "Italian" ) OR EXCLUDE ( LANGUAGE , "French" ) OR EXCLUDE ( LANGUAGE , "Chinese" )).

After identifying the related documents, the following articles are excluded based on the PRISMA method as shown in fig. 1

## Descriptive Analysis

### Year-Wise Analysis

Figure 2 presents the year wise development of Algorithmic trading. The Algorithmic trading has gained a significant attention in last decade only, the first publication on Algorithmic trading in Scopus database year back to 2007. During 2007 to 2011 a limited attention has been paid to this area of research. The total number of publications during this phase was restricted to 16. There after the Algorithmic trading has witnessed an exponential growth, the year 2020 with 53 publications and year 2024 with maximum 60 publications and year 2023 with 56 publications respectively.

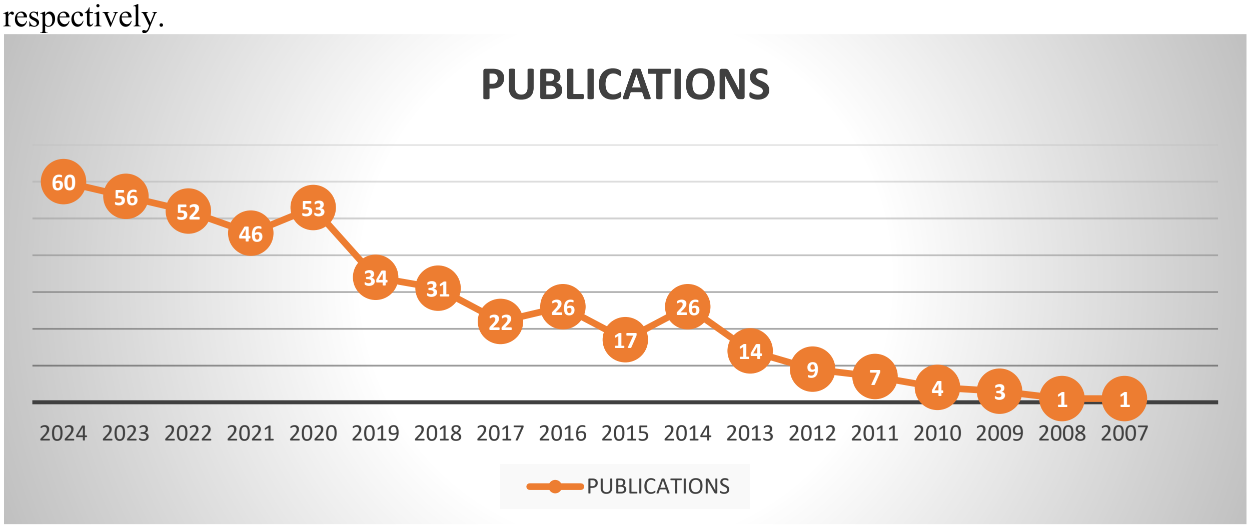


**Figure 2: Year-wise Publications on Algorithmic trading**

Figure 2 indicates a sharp increase in algorithmic trading research after 2010, reflecting the growing academic response to the expansion of high-frequency trading and ai-based trading systems. The peak in 2024 suggests sustained scholarly interest in this domain.

**Country-Wise Analysis**

Research on algorithmic trading has garnered global attention, with contributions coming from a diverse range of countries. According to data from the Scopus database, scholars from 58 different nations have contributed to the body of literature in this field. Figure 3 presents an overview of the countries with the most substantial research output related to algorithmic trading. The United States leads the way with 118 publications, reflecting its dominant role in both financial markets and academic research. The United Kingdom follows closely with 89 publications, securing the second position. Canada, with 44 publications, and India, with 41, also demonstrate strong engagement in this domain, indicating a growing interest and active research environment in these regions.

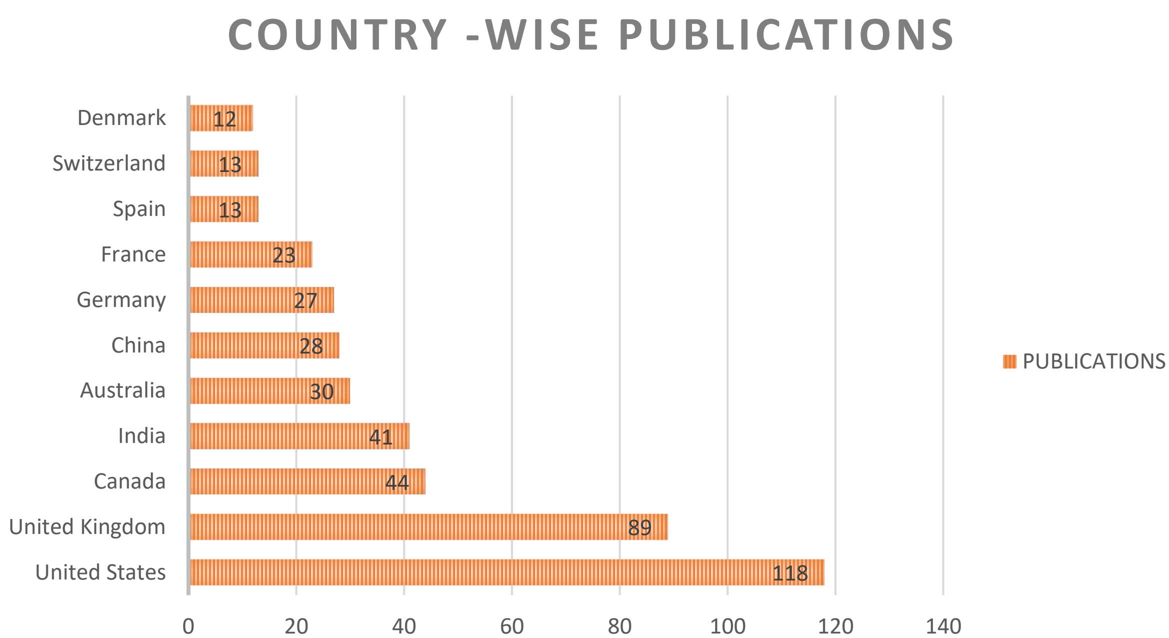


**Figure 3: Country –wise publications on Algorithmic trading**

Figure 3 highlights the dominance of developed financial markets in algorithmic trading research, with the United States and the United Kingdom leading both in volume and influence. The rising contribution from countries such as India and Canada reflects the globalization of research in this field.

**Source-Wise Analysis**

Figure 4 provides the source-wise analysis of the documents. Journals dominate the sources, making up 85% of the total, indicating a strong reliance on peer-reviewed academic literature. Conference Proceedings account for 14%, suggesting some consideration of recent research presented at conferences. Trade Journals and Book Series each contribute 1% or less, indicating minimal influence in the study.

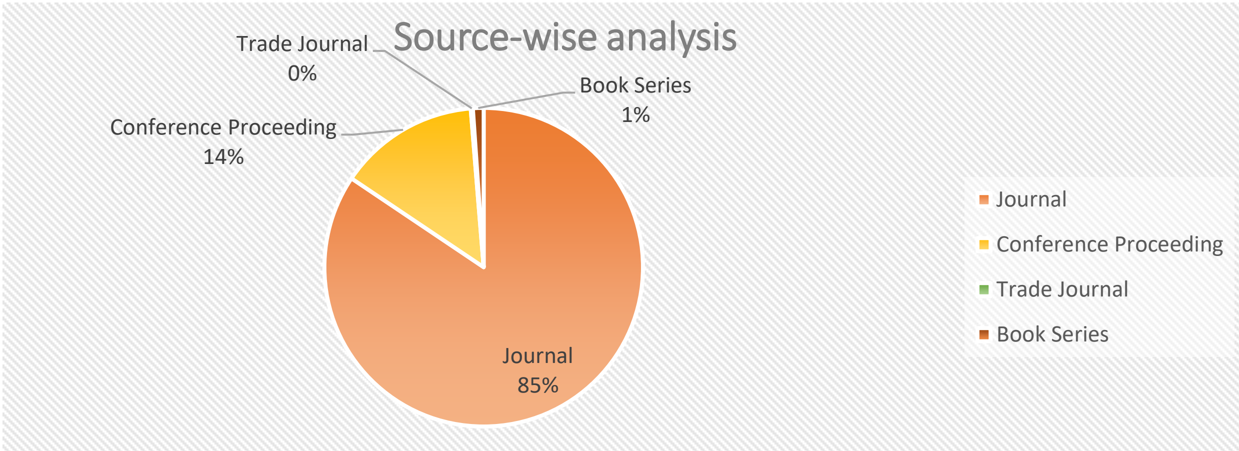


**Figure 4: Source-wise Analysis**

Figure 4 shows that journal articles constitute the primary outlet for algorithmic trading research, indicating that the field has matured into a well-established academic discipline rather than being driven mainly by conference or practitioner publications.

**Author-Wise Analysis**

In the field of Algorithmic trading, the Scopus database recognizes the contribution of 159 authors. Here, it is worth referring that out this list only five authors have contributed 5 or more manuscripts. Figure 5 highlights the top ten authors in the field of Algorithmic trading. Jaimungal, S., has 23 publications and is at the top of leader board followed by Cartea, Á., with 19 publications.


**Figure 5: Top Ten Authors in the field of Algorithmic Trading**

Figure 5 reveals that research output is concentrated among a small group of highly productive scholars, suggesting the presence of core contributors who shape the intellectual direction of algorithmic trading studies.

Overall, the descriptive analysis reveals a rapidly expanding and increasingly international body of research on algorithmic trading. Publication trends show strong growth in the last decade, led primarily by developed economies with advanced financial markets. Journals dominate as the main outlet for scholarly communication, indicating the consolidation of this field within mainstream finance and technology research. At the author level, a limited number of highly productive scholars account for a substantial share of contributions, reflecting the emergence of core research leaders. Together, these findings provide a foundation for the subsequent network analysis by establishing where, by whom, and in what outlets algorithmic trading research is most actively produced.

## Network Analysis

### Citation of Authors

To analyze citation networks within the field of algorithmic trading, the study applied a criterion requiring each author to have at least one publication and at least one citation. Additionally, the analysis was stratified by publication year to understand temporal trends. The results revealed that 415 authors formed interconnected citation networks, grouped into 95 clusters. These networks exhibited a total of 2,039 links, with an overall link strength of 2,470—indicating a dense and collaborative research landscape.

Among the most influential contributors, Hendershott emerged as the most cited author, with 1,002 citations. He is followed closely by Albert J. Menkveld and Charles M. Jones, each with 790 citations. A closer look at the temporal distribution of citation activity shows that most of these author-to-author citation connections occurred between 2014 and 2024, reflecting the growth and intensification of scholarly engagement with algorithmic trading in the last decade.

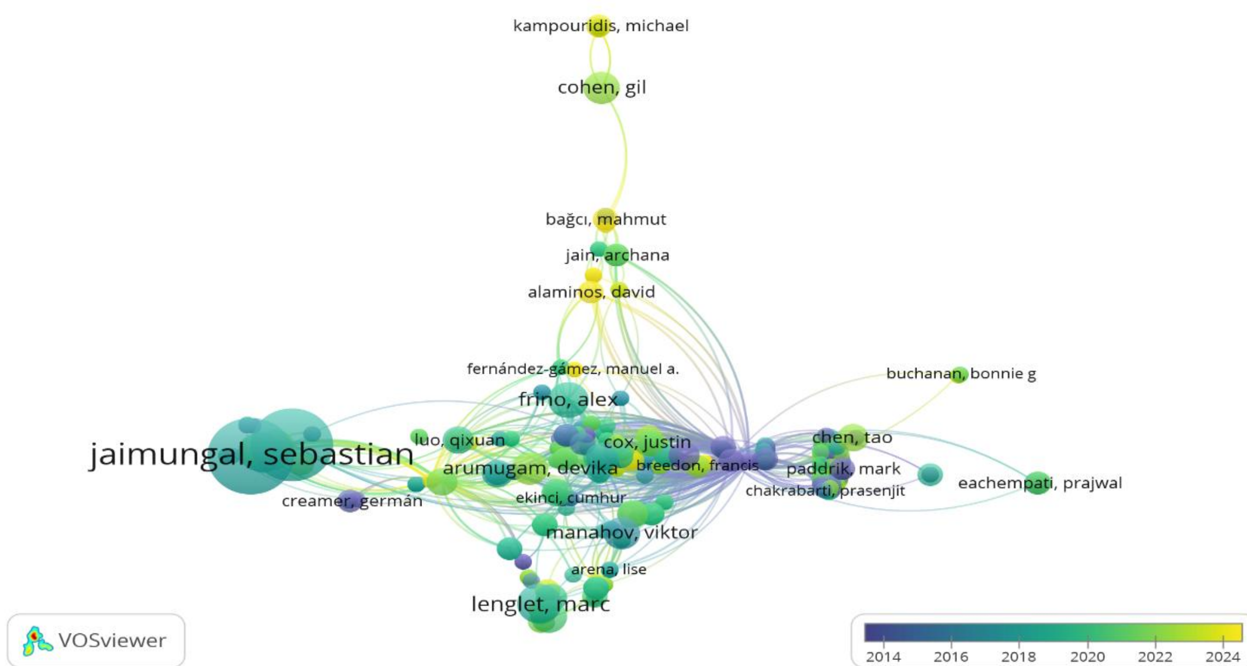


**Figure 6: Status of authors' attribution links by year**

### Citation of Countries

To assess the year-wise distribution of country-level citations, the analysis considered only those countries with at least one publication and one citation in the dataset. Based on this criterion, 50 countries were identified as having interconnected citation relationships. These were grouped into 16 clusters, forming 240 citation links and a total link strength of 969, indicating notable collaboration and influence across nations.

The countries with the highest citation counts were the United States, leading with 3,550 citations, followed by the United Kingdom with 1,440 citations, and Canada with 989 citations. When considering publication volume, the USA also ranked first with 117 publications, followed by the UK (89 publications) and Canada (44 publications), highlighting their central roles in shaping research in algorithmic trading.

Interestingly, when analyzing the temporal distribution of these citation links, it was found that the majority of country-based citation activity occurred between 2018 and 2022, suggesting a recent surge of global scholarly interest and collaboration in this domain.

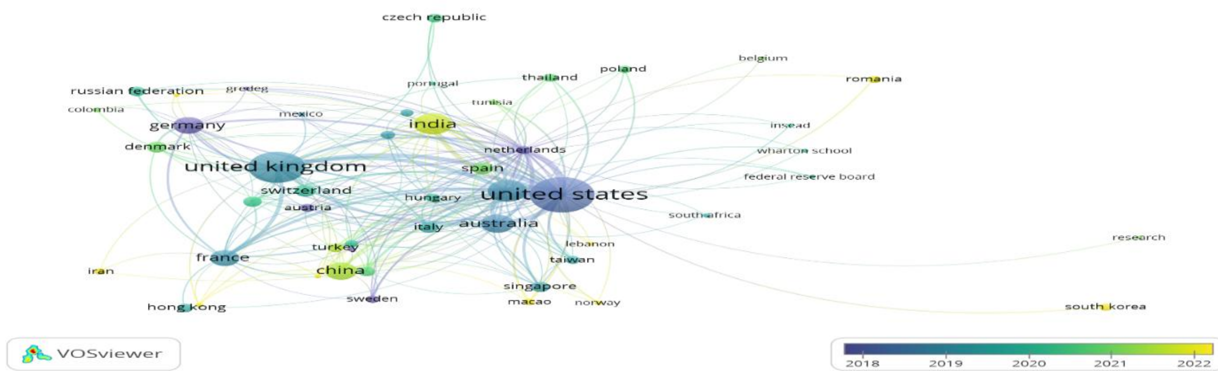


**Figure 7: Stratification of countries' attribution connects by year**

**Bibliographic Coupling by Authors**

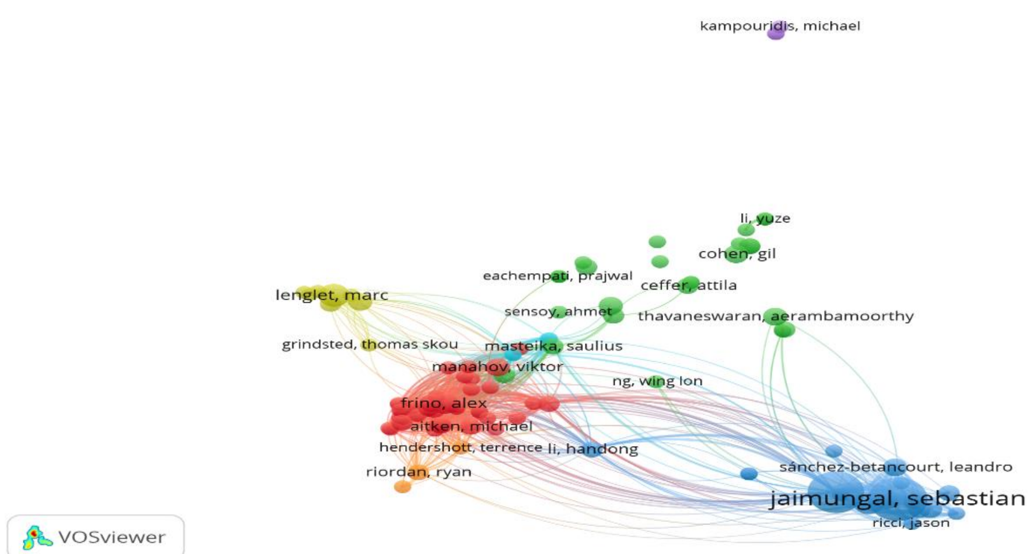


**Figure 8: Bibliographic Coupling by Authors**

Figure 11 is a network diagram illustrates the connections between authors based on their research papers and citations. Out of 1024 authors, just 100 fulfilled the requirement of having a minimum of 2 documents and 4 citations, which signifies their elevated productivity and impact. The nodes symbolize the authors, with larger nodes indicating more substantial influence. The connections between the nodes represent co-authorships, while various colors signify groups of authors who collaborate more often. Prominent authors such as " Hendershott " and "Jaimungal, Sebastian" occupy central positions in the network, highlighting their important contributions to the research community. The diagram showcases a collaborative and interdisciplinary research atmosphere.

**Co-Authorship of Authors**

To explore collaborative patterns among researchers, a co-authorship analysis was conducted, considering only those authors with minimum one publication and one citation. The resulting network map, shown in Figure 8, highlights the most interconnected authors in the field of algorithmic trading. The analysis identified 10 clusters, comprising 43 co-authorship links and with the overall strength of the relationship of 73, indicating moderate levels of collaboration within the research community.

Among these authors, Terrence Hendershott stands out as the most cited, with 1,002 citations, underscoring his influence in the field. He is followed by Albert J. Menkveld, who has received 790 citations. These citation counts not only reflect individual academic impact but also emphasize the central roles these scholars play within the co-authorship network.

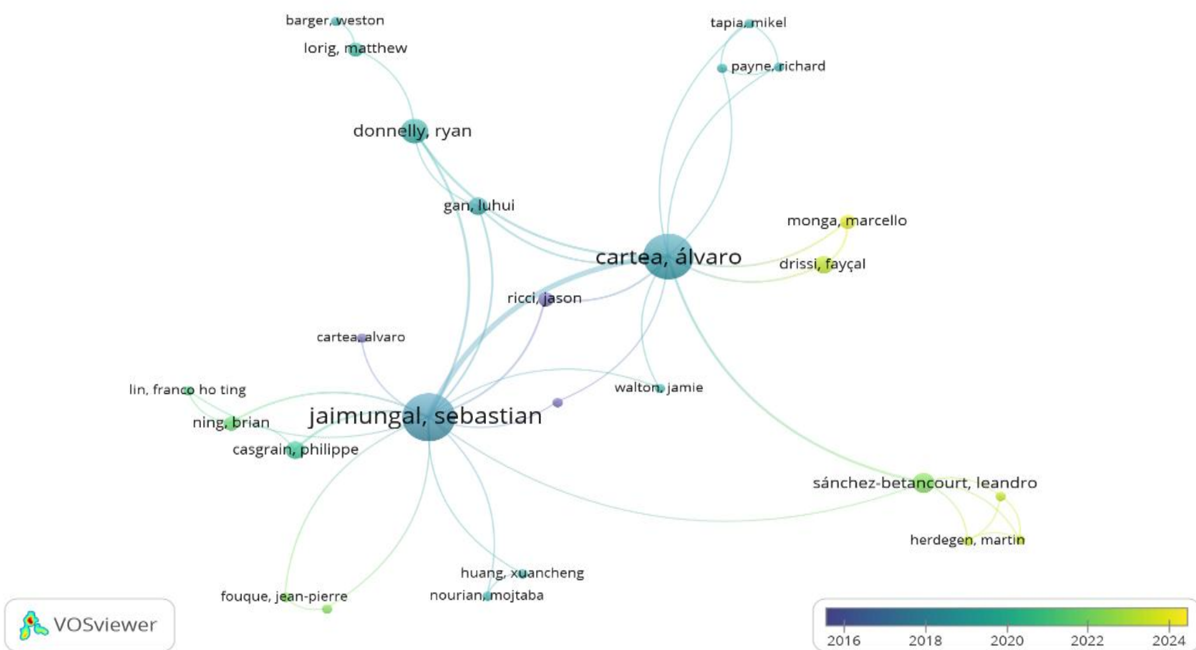


**Figure 9: Co-Author Connects Demonstrating Collaboration Between**

**Citation of Organizations**

To examine how academic institutions are interconnected through shared bibliographic references, a stratified analysis of bibliographic coupling was conducted. The analysis included institutions that had published at least one study and received at least one citation. A total of 398 institutions were identified as having relational ties, which were organized into 83 clusters, forming 1,879 links with a total link strength of 1,947. These connections highlight the extent to which algorithmic trading research is both widespread and deeply rooted across institutions globally. Such linkages also reflect the growing acceptance and scholarly depth of this research domain.

Among the institutions contributing notably to this field are the University of Toronto, Canada, and the University of Washington, Seattle, USA, each with four publications. In terms of citation impact, the most cited institutions include Columbia Business School (USA), the University of California, Berkeley (USA), and VU University Amsterdam (Netherlands)—each with 790 citations. Sage Hall, Cornell University also made a significant impact with 301 citations. When it comes to institutional link strength, Columbia Business School, the Haas School of Business at the University of California, and VU University Amsterdam share the highest total link strength of 232 each, indicating strong bibliographic ties and influence. The University of Ontario also stands out with a link strength of 109.

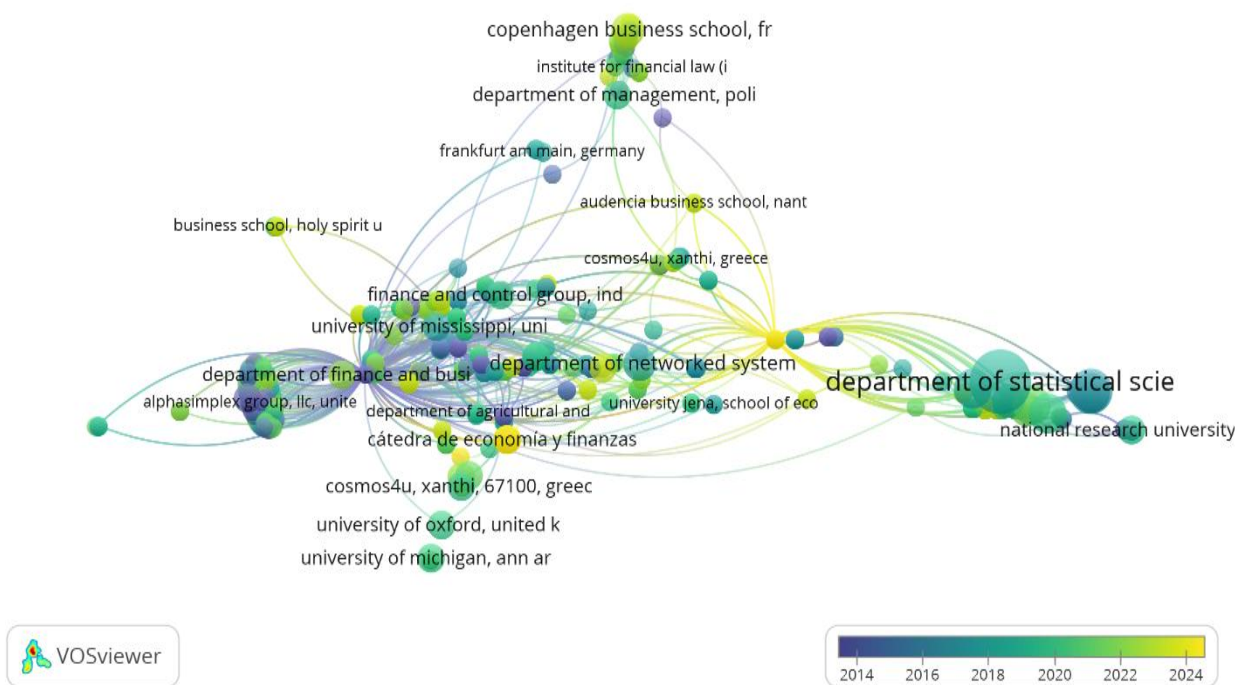


**Figure 10: Stratification of bibliographic match connections of institutions by year**

## Co-Occurrence of Keywords

The keywords most used in publications related to the concept of "Algorithmic trading" have at least two relationships: "Algorithmic trading" has 298 repetitions with a total link strength of 1747, "High frequency trading" has 73 repetitions with the overall strength of the relationship of 376, and "Commerce" has 63 repetitions with the overall strength of the relationship of 681. "Financial market" appears 48 times with 695 total link power, and "electronic trading" appears 46 times with 677 total link strength. 31 clusters with 12884 linkages and with the overall strength of the relationship of 15159 were discovered after the investigation.

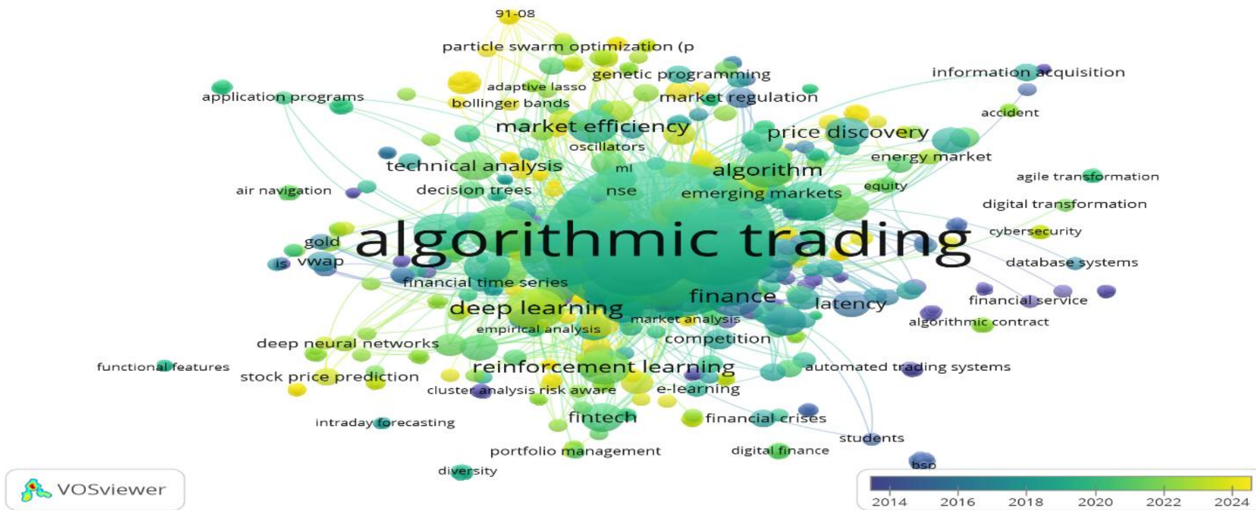


**Figure 11: Layering of the year-over-year most popular keyword links**

The clusters identified in the network diagrams represent distinct yet interconnected knowledge domains within algorithmic trading research. Certain clusters are primarily associated with market microstructure and liquidity effects, reflecting foundational work on how algorithmic trading influences price discovery and volatility. Other clusters emphasize strategy development using machine learning and artificial intelligence, indicating a methodological shift toward data-driven and adaptive trading systems. A further set of clusters is oriented toward regulatory and governance issues, highlighting growing scholarly concern over market fairness, transparency, and systemic risk. Together, these clusters reveal that the intellectual structure of the field is organized around three core pillars: market behavior, algorithmic strategy design, and regulatory oversight, with increasing integration across these domains over time.

## Results and Discussion

### Publication Trends

Research on AT has grown significantly since 2010, correlating with advances in HFT and AI-driven trading strategies. The highest number of publications was recorded in 2024 (60 studies).

### Key Contributors

- **Top Contributing Countries:** USA (118 papers), UK (89), Canada (44), India (41),
- **Most Cited Authors:** Hendershott (1002 citations), Menkveld (790), Jones (790).
- **Top Institutions:** Columbia Business School (790 citations), University of California (790), VU University Amsterdam (790).

### Emerging Themes

Bibliometric keyword analysis reveals the most frequently occurring terms:

- Algorithmic Trading (298 occurrences, 1747 total link strength)
- High Frequency Trading (73 occurrence, 376 total link strength)
- Commerce (63 occurrences, 681 link strength)
- Financial Markets (48 occurrences, 695 link strength)
- Electronic Trading (46 occurrences, 677 link strength)

The bibliometric findings can be interpreted in light of broader transformations in financial markets and trading infrastructures. The rapid growth of publications after 2010 coincides with the expansion of high-frequency trading, electronic market platforms, and the availability of large-scale financial data, indicating that academic research has evolved alongside market digitization. The prominence of artificial intelligence and machine learning within keyword clusters reflects a structural shift from execution-oriented algorithms toward predictive and adaptive trading systems capable of processing complex and high-frequency information flows. This shift mirrors developments in financial markets where competitive advantage increasingly depends on data analytics and automation rather than human discretion alone. At the same time, the growing visibility of regulatory and governance-related themes suggests that technological innovation has outpaced existing institutional frameworks, generating concerns over market stability, transparency, and systemic risk. The convergence of technological and regulatory clusters implies that future research will likely focus on balancing innovation with oversight, positioning algorithmic trading at the intersection of financial modernization and public policy.
These themes highlight the interdisciplinary nature of algorithmic trading research, integrating finance, computer science, and regulatory perspectives.

**Table 1: Summary of Key Findings in Algorithmic Trading Research**

| ***Aspect*** | ***Key Findings*** |
|---|---|
| *Publication Growth* | Research increased significantly post-2010 due to advances in AI & machine learning. |
| *Top Contributing Countries* | USA (118 papers), UK (89), Canada (44), India (41), |
| *Most Cited Authors* | Hendershott (1002 citations), Menkveld (790), Jones (790). |
| *Keyword Trends* | "Algorithmic Trading" (298 occurrences), “High Frequency Trading” (73 occurrences) "Commerce" (63), “Financial Market” (48 occurrences) "Electronic Trading" (46 occurrences). |
| *Top Research Themes* | Market efficiency, high-frequency trading, AI-driven trading, regulatory impact. |

## Conclusion

**Bibliometric Study on Algorithmic Trading: A Scopus-Based Analysis (2000–2024)**

Using bibliographic data retrieved from the Scopus database for the period 2000–2024, this research presents a systematic bibliometric assessment of studies related to algorithmic trading. A total of 462 English-language publications, including journal articles, conference papers, trade journals, and book series, were analyzed using VOSviewer (version 1.6.20). To find important themes, trends, and research patterns, the analysis concentrated on the titles, abstracts, and keywords.

**Keyword Patterns and Thematic Clustering**

One of the core objectives was to analyze recurring keywords to map the thematic landscape of the literature. Keywords that appeared at least twice were considered. Not surprisingly, Algorithmic Trading emerged as the dominant term, occurring 298 times with a strong total link strength of 1,747. Other frequently appearing terms included High-Frequency Trading (73 occurrences), Commerce (63), Financial Market (48), and Electronic Trading (46). In total, 12,884 keyword co-occurrence links were identified, forming 31 thematic clusters and indicating strong interconnections among research topics in this field.

**Trends Over Time**

The publication trend suggests that scholarly interest in algorithmic trading picked up after the mid-2000s, with the earliest relevant work appearing in 2007. Interest continued to grow steadily, peaking in 2024 with 60 publications—the highest in any single year.

**Publication Types and Most Active Authors**

J ournal articles made up the bulk of the research output (85%), followed by conference papers (14%), with only a small portion coming from trade journals or books. In terms of author contributions, S. Jaimungal led with 23 publications, followed by Á. Cartea with 19.

**Author Influence and Citation Impact**

Citation analysis was conducted with a threshold of a minimum of one citation and publication. The network revealed 415 connected authors, forming 95 clusters with 2,039 citation links. Among these, Terrence Hendershott stood out as the most cited author, with 1,002 citations. Albert J. Menkveld and Charles M. Jones followed closely, each with 790 citations. Most of the citation activity occurred between 2014 and 2024, reflecting a decade of intensified scholarly interaction.

**Global Research Contributions**

Country-level analysis showed contributions from 50 countries, grouped into 16 clusters and connected by 240 citation links. The US led both in publication count (117) and total citations (3,550). The UK (89 publications; 1,440 citations) and Canada (44 publications; 989 citations) also featured prominently. The majority of cross-country citation links were active during the 2018–2022 period.

**Policy, Academic, and Theoretical Implications**

Theoretically, the study clarifies the intellectual structure of algorithmic trading research by demonstrating how thematic clusters evolve alongside technological change. Academically, the findings help identify influential authors, institutions, and dominant research themes, thereby supporting focused literature reviews and collaborative research. From a policy perspective, the prominence of high-frequency trading and regulatory themes highlights the importance of evidence-based oversight to mitigate systemic risks while fostering financial innovation.

**Future Research Frontiers**

The bibliometric mapping identifies several emerging research directions, including deep reinforcement learning in trading systems, the role of algorithmic trading in market resilience during periods of financial stress, and comparative analyses of regulatory frameworks across countries. Future studies may also examine ethical issues, algorithmic transparency, and the societal impact of automated trading, extending the literature beyond descriptive analysis toward theory-driven and policy-oriented inquiry.

## Limitations

A key limitation of this study is its exclusive reliance on the Scopus database, which may result in the omission of relevant publications indexed in Web of Science, Google Scholar, or discipline-specific repositories. Consequently, certain technical or region-specific contributions may not be fully captured. Future studies could address this limitation by conducting comparative multi-database analyses to assess the robustness of bibliometric patterns and enhance the representativeness of the finding.

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# Does ESG Influence Dividend Policy? Evidence from India

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## Abstract

Sustainability remains a prominent topic of discourse among individuals, investors, and corporate executives alike. There is a growing recognition that investors are now incorporating financial performance considerations alongside environmental and social factors. This research endeavour aims to thoroughly examine the complex relationship between corporate sustainability, assessed through Environmental, Social, and Governance (ESG) disclosure scores, and dividend policies within the Indian business environment. Methodologically, the research adopts a quantitative approach, relying on secondary data to make objective and generalised findings. The research strategy focuses on the Nifty 500 index, which spans from 2014-2022, making the Indian market its geographical focus point. The final sample includes 231 firms carefully gathered from the Bloomberg database. Employing a GMM model, the research outcomes indicate a significant and positive relationship between lagged ESG disclosure scores and dividend policy, which highlights the importance of previous year scores on the current year cash distributed to the shareholders. This implies companies operating within the Indian market are still in the nascent phase of incorporating ESG considerations into their decision-making processes, including dividend distribution. However, investors must look for the ESG practices of the firms while making any decision.

**Keywords**: ESG Disclosure Score, Dividend Policy, Agency theory, Sustainability

## Introduction

The strategic decisions around sustainability by businesses have gained importance, and their impact on the creation of sustainable trends and policies cannot be overstated (Robert & Broman, 2016). Over time, sustainable investing has shown an upward trend. In today's time, sustainability measures such as Environmental, Social, and Governance (ESG) have become of utmost importance on the agenda for investors when making any decision. It all started with SRI which delved into value-based creation. As SRI evolved, transmission happened from ethics to more inclusion of ESG issues into decision choices, resulting in consideration of ESG strategy in the form of ESG reporting by the firms. It is commonly understood that the function of companies has grown in importance in the contemporary era as their effect on the ecosystem has grown. As economic and industrial growth continues, the increasing threat of climate-related risks has elevated the concept of sustainability to a broader and more significant level.

ESG has its origins in United Nations programs, which began in this area in 2004. The term ESG gained prominence with its initial usage in a seminal research publication named "Who Cares

Wins," which was published in 2004 by the Global Compact [1]. The report claims that integrating ESG issues into capital markets makes sound financial sense, promotes more sustainable markets, and improves societal outcomes. The UNEP also released the "Freshfield Report" at the same time, demonstrating the significance of ESG issues for financial value.

ESG reporting in India began in the year 2009 when the Ministry of Corporate Affairs (MCA) publicised the Voluntary Guidelines on CSR. And, with the advent of Business Responsibility Reporting, Corporate Social Responsibility, National Guidelines on Responsible Business Conduct (NGRBC), and the recently adopted Business Responsibility and Sustainability Report (BRSR), reporting has gone a long way. The Securities and Exchange Board of India (SEBI) obligated the top 100 listed businesses to publish their ESG activities through a 'Business Responsibility publish' in a circular issued on August 13, 2012[2].

Since November 2015, Business Responsibility Reporting has been expanded to the top 500 listed firms on the BSE and NSE based on market capitalization. From FY 2022-2023, the top 1000 listed businesses by market capitalization must submit BRSR [3]. With increasing ESG investments, SEBI's disclosure through BRSR has been put up to become more open with such strategic investment decisions while also fulfilling growing concerns about greater corporate governance and environmental stewardship.

As investors become more aware of their responsibilities to the environment and society, companies are pressured to provide information about the detrimental effects of their actions in these areas. To determine the long-term profitability of their investments, investors are becoming more responsible and are looking for ESG compliance reports. Because investors are interested, companies have incorporated significant ESG issues into their due diligence procedures. As investors' interest in ESG investing grows, so does corporate adoption of ESG reporting. Weber et al., (2014) talk about the significance of ESG disclosure, established on the three main principles: stakeholder management, accountability, and institutional theory. Corporate participation in ESG practices is prompted by institutional incentives, which form the basis of ESG reporting. Businesses report on ESG issues because they are responsible to their stakeholders.

Numerous researchers have made extensive efforts to investigate both financial and non-financial factors that drive ESG initiatives. (Brooks & Oikonomou, 2018; Aboud & Diab 2018; Farooq et al., 2015; Dangwal & Sharma, 2014; Balatbat et al., 2012). While there is enough evidence globally investigating environmental practices, social factors and governance mechanisms individually, few studies has been aimed at understanding the Indian setting, despite its significant global competitiveness. In India, the ESG investments are still in their early stages. The country's current policy has actively focused on the climate friendly initiatives and private sector involvement in becoming greener. The 2023 Indian budget has also prioritized Green Growth to establish a greener and more sustainable India, committing INR 350 billion ($4.3 billion) to energy transition and Net Zero goals [4].

Corporations have made significant progress over the years, yet evidence indicates that their social and environmental performance is still lacking. Research has shown a clear relationship between CSR and equity (Chen et al., 2016). Additionally, companies with high ESG ratings frequently have lower capital costs (Ghoul et al., 2011), and investments in ESG initiatives usually result in higher stock values (Friede et al., 2015). On the other hand, research on the debt side has also been done, with an emphasis on the connection between credit risk and ESG variables (Henisz & McGlinch, 2019). Notably, ESG scores and the COD have been found to be inversely correlated (Arora, 2022).

## Rationale of the Study

The importance of sustainability as a prominent trend in financial markets today cannot be overstated. The notion of firms being cognizant of and sensitive to, their influence on society and the environment is gaining traction. Several academics and researchers are presently exploring various elements of ESG. Some of the studies explained how the composition of a company's board of directors can affect its ESG performance (Iqbal & Mallikarjunappa, 2011; Barberis et al., 1998), whereas some focus on ESG scores and their impact on the firm value (Yoon et al., 2018; Birindelli et al., 2018). Several researchers have described how the stakeholder should consider sustainability factors when making investment decisions (Cao et al., 2019; Humphrey et al., 2012). When environmental resource utilization is mismanaged, it fails to achieve objectives and can result in value destruction for companies and shareholders. However, the implementation of sustainable strategies often yields positive effects, particularly through signalling theory. Shareholders and stakeholders may prioritize the ethical implications of such actions over short-term financial costs.

Nonetheless, higher environmental and social practices necessitate greater investments to drive long-term value creation. Additionally, achieving environmental protection goals can lead to cost reductions, such as lower taxes and operational expenses, thereby increasing available cash flow through savings from sustainability practices. However, investment decisions divert free cash flow from shareholders. Hence, the author has undertaken the following research to explore these dynamics further. Examining the effect of ESG on wealth distribution through dividend policy is essential, as dividends are the most widely utilized means of shareholder payout.

Primarily for this purpose, this study aims to understand the relationship between ESG disclosure scores and the dividend policy in India. In contrast to the US and other international markets where there have been a lot of ESG studies, Indian ESG research is in its early stage. By investigating this relationship, conclusions can be drawn on how the presence of ESG implementation influences the dividend payout of Indian companies. The exploration of the relationship between firms' decisions and ESG scores has thus far overlooked the dividend decision.

The subsidiary motive is to assess how the three individual dimensions of ESG have an impact on dividend policy. It can also be a case that a different degree engages in individual E, S, and G activities. For instance, a company can be very committed to eco-friendly practices but less so about the social and/or governance aspects of ESG. To gain a better understanding of the effect of ESG scores on a firm's corporate finance decisions, a more fine-grained examination of ratings may be useful.

The purpose and background of the problem lead to the following research question:
“What is the relationship between ESG disclosure scores and the dividend policy in India?”

The remainder of this paper is organized as follows: Section 2 gives a comprehensive review of the material literature and outlines the development of our hypotheses. Section 3 details the sample and research methodology. Section 4 presents the findings and analysis. Lastly, Section 5 offers a summary of the study and concludes.

## Review of Literature

### Theoretical Background

### Agency Theory

The dividend policies are examined from the standpoint of the agency problem using agency theory. As suggested by Jensen and Meckling (1976), increasing dividends would intensify the external capital market's oversight function, as an agency's cost increases with a fall in the internal equity ratio. Fama and Jensen (1986) expanded on this idea by asserting that managers can lower their agency costs by implementing dividend policies.

The work of Barnea & Rubin (2017) argued that managers have an interest in investing in such activities because it makes them look socially responsible, and can be used to connect the agency theory problem to ESG activities. It further leads to agency costs, as managers might overinvest in ESG investments to focus on their private gain (Baron et al., 2006). However, agency costs can be managed if the cost of managers contributing to their goods is offset by a fall in the value of their income (Baron et al., 2006).

Based on the aforementioned facts, the business can restrict the management's overinvestment in ESG efforts by providing dividends, which reduces the excess free cash available to the manager (Benlemlih, 2017).

**Stakeholder Theory**

The primary premise of the stakeholder theory asserts that organizations should not solely prioritize the interests of their shareholders but should also take into account the needs and concerns of all other stakeholders involved (McWilliams et al., 2006). According to this hypothesis, managers may transfer less cash to the shareholders via dividends to focus on other stakeholders.

An excellent ESG score combined with a consistently high dividend distribution demonstrates that a company is concerned about all of its stakeholders (Benlemlih, 2019). Firms might opt to reduce the financial resources allocated for dividend payments to allocate additional funds toward enhancing their ESG ratings. (Zahid et al., 2022; Ghoul et al., 2011; Dhaliwal et al., 2011).

**Relationship between ESG disclosure scores and Dividend policy**

There is a tonne of studies on sustainability that concentrate on how it affects company performance in the body of existing literature. In comparison to create an understanding between sustainability and financial performance, the literature on dividends is very limited. Better ESG practices demonstrate a company's focus on both shareholders and stakeholders by upholding their obligations to all the parties (Zahid et al., 2023).

Barros et al. (2023) explore the impact of ESG scores on the dividend policy of the U.S high tech companies for, 2002-2021 and claim that high ESG rating firms scores tend to exhibit a propensity for dividend payments. Despite more funds required for technological R&D, they feel pressure from the shareholders to pay dividends. they further reported that managers who look at paying dividends as an indication of increased transparency can get additional advantages due to high ESG ratings.

Matos et al. (2022) suggest a direct positive link between the ESG scores and stability of dividends for a sample of European firms. Furthermore, both environmental and governance scores exhibit parallel relationships with the overall score. The authors further attempt to establish the role of ESG scores on the dividend yield and they found the same results as others.

Jung & Kim (2021) aim to understand how ESG factors relate to dividend policies in Korean firms. Their research finds that ESG scores affect different dividend measures differently. Specifically, social ratings positively influence the dividend payout ratio, while overall ESG ratings positively affect dividends measured by dividend rate and dividend yield. Since Korean firms generally have low dividend payout ratios, enhancing ESG activities could potentially increase dividend payments. These findings are supported by agency theory and the life cycle hypothesis. Moreover, companies with stronger ESG performance may reach their target dividend levels more swiftly.

The study conducted by Oh and Park (2021) aimed to examine the relationship between Corporate Sustainable Management (CSM) and dividend payout, drawing on agency and signalling theories. They also explored whether affiliation with a chaebol group influences this relationship. This research is valuable as chaebol group managers, typically majority shareholders, may mitigate agency issues. Regression analysis revealed a significant positive association overall. However, firms within the chaebol group did not exhibit the same outcomes, indicating that increased investment suitability within chaebol groups may reflect stakeholder preferences rather than shareholder interests.

On the contrary, in a study by Niccolo et al. (2020), the focus was on the influence of ESG strategies on dividend payout within the Chinese market, given their significance in the global economy. The study encompassed the largest 300 companies listed on the Shanghai and Shenzhen stock exchanges. The results revealed that engaging in ESG practices diminishes free cash flow for shareholders, resulting in a decline in dividend payout. Specifically, environmental and social scores also notably and adversely affect payout policy. The authors propose that considering these mechanisms imposes costs on shareholders by diverting their resources. This study underscores the challenge for managers in balancing the interests of both shareholders and stakeholders in the context of sustainability imperatives.

Ni & Zhang (2019) analysed, a shift in relative power toward stakeholders is more likely in companies with debilitated corporate governance structures, where shareholders lack sufficient mechanisms to protect their interests against stakeholder influences. These factors all contribute to the more pronounced negative relationship. The evidence suggests that the enforcement of regulations intended to enhance the effectiveness of information exchange between stakeholders and shareholders may reduce the revenue generated by the company for its shareholders.

Benlemlih (2019) attempted to examine the influence of CSR levels on a firm’s dividend payout policy in an American setting where the author used two arguments to describe the relationship i.e., agency theory and signalling theory between these two. While the signalling theory connected them through dividend announcement signals, the agency theory explains the connection through the overinvesting hypothesis, which postulates that managers may allocate a larger portion of their free cash reserves to investments to maximize their compensation.

Cheung et al. (2016) conducted a study to examine the relationship between sustainability performance and dividends. The link is shown from two perspectives on dividends: "the equity cost of the capital channel" and "the earnings channel". The first viewpoint shows how sustainability activities can result in a lower COE (Ghoul et al., 2011). As a result, businesses decide to invest or hold onto cash rather than distribute dividends. Additionally, the author argues that a reduced cost of capital increases the incentives for businesses to hoard cash since it lowers the opportunity cost. Firms may invest more when the capital cost is lower as are less constrained by financial limitations, which means there is less to distribute in the form of dividends. Contrary to the second viewpoint sustainable activities can result in more earnings with a lower level of risk.

**Objectives**

The primary objective of this study is to examine the relationship between ESG scores and dividend policy. To correctly ascertain that the ESG performance has any influence on the dividend payout ratio, the combined scores and individual scores will be considered. Thus, the goals of this research are as follows:

1. The first aim of this study is to investigate the effect of composite ESG scores on dividend policy in India
2. The second aim of this study is to ascertain the effect of individual component scores on dividend policy in India.

**Hypotheses**

Based on the above objective, the following hypotheses have been formulated and tested in this regard:

$H0_1$: There is no significant relationship between the combined ESG score and the dividend payout ratio of Indian firms.

$H0_2$: There is no significant relationship between the Environmental score and the dividend policy of Indian firms.

$H0_3$: There is no significant relationship between the Social score and the dividend policy of the Indian firms.

$H0_4$: There is no significant relationship between the Governance score and the dividend policy of Indian firms.

## Research Methodology

**Sample**

This study is centered on the Indian market as its geographical focus. The selected index for this study is the Nifty 500. The period under analysis is from 2014 until 2022 including 500 firms. Financial firms are excluded from the sample due to their unique regulatory requirements and distinct approaches to dividend distribution, investment strategies, and different sector-specific regulations. This study specifically examines the influence of ESG on dividend levels, corporates that didn’t pay out dividends for not even a single period of the study and companies that don’t have disclosure scores have been removed from the sample. The non-dividend-paying firms have been excluded as they can distort the objective of this study. Although it may create a bias, it is necessary to create a more meaningful and relevant result. Consequently, the final sample comprised 231 firms, yielding a total of 2,079 firm-year observations.

**Source of Data**

The data is retrieved from Bloomberg, which is secondary data and varies from 2014 to 2022. The Bloomberg ESG disclosure scores have been used for this study's measurement. The disclosure ratings for E, S, and G range from 0 to 100, indicating no disclosure to full disclosure. The ratings are then combined using a proprietary algorithm into a single ESG disclosure score (ranging from 0 to 100).

**Variables**

A measure of dividend has to be selected to measure how ESG scores influence the dividend policy. The most commonly used measure is the dividend payout ratio. Many studies see dividend payout as a reliable indicator when evaluating the effects of specific corporate factors on dividends (Niccolo et al., 2020; Chen et al., 2017).

This study also controls for some variables that may be crucial in understanding the dynamics of dividend policy, as identified in prior research. Firm Size (fs), represented by the natural logarithm of total assets, is included as a variable because larger firms typically have greater access to capital markets, more diversified operations, and more established reputations, which can influence their dividend policies and ESG practices (Benlemlih, 2019). Financial leverage (fl), the ratio of total liabilities to total assets, is considered as highly leveraged firms that may be constrained in their ability to pay dividends due to debt obligations, prioritizing debt servicing over dividend distribution (Limriangkrai, 2016). Return on Assets (roa), is anticipated to positively impact dividend payouts, reflecting the firm's ability to generate income from its assets which signals strong financial health to the investors (Miller and Rock, 1985; Solberg and Zorn, 1992). Finally, corporate governance characteristics, such as Board Independence (BI) and Board size (bs), are incorporated to account for their influence on dividend policies by mitigating agency conflicts and managerial opportunism (Daoud Ellili, 2022; Zahid et al., 2022; Guizani, 2018). All the variables are listed in Table 1.

**Table 1: Variables**

| SYMBOL | VARIABLES | | SOURCE |
|---|---|---|---|
| esgds | ESG Disclosure score | Independent Variable | Bloomberg |
| eds | Environmental Disclosure Score | Independent Variable | Bloomberg |
| sds | Social Disclosure Score | Independent Variable | Bloomberg |
| gds | Governance Disclosure Score | Independent Variable | Bloomberg |
| dpr | Dividend Payout Ratio | Dependent Variable | Bloomberg |
| fs | Firm Size | Control Variable | Bloomberg |
| bs | Board Size | Control Variable | Bloomberg |
| roa | Return on Assets | Control Variable | Bloomberg |
| fl | Financial Leverage | Control Variable | Bloomberg |
| bi | Board Independence | Control Variable | Bloomberg |
| fcf | Free cash flow | Control Variable | Bloomberg |

Source: Author’s calculation

**Empirical Model**

This study employs two distinct models to assess the influence of ESG practices on a firm's dividend payout. The first model examines the overall effect of ESG strategies, while the second model dissects its components, namely environmental, social, and governance factors.

For the first objective, the first model would be:

$$dpr_{it} = \beta_0 + \beta 1esgds(t\text{-}1)it + \beta_2 fs_{it} + \beta_3 fcf_{it} + \beta_4 roa_{it} + \beta_5 fl_{it} + \beta_6 bi_{it} + \beta_7\ bs_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

For the second objective, the second regression model would be:

$$dpr_{it} = \beta_0 + \beta_1 eds(t\text{-}1)_{it} + \beta_2 sds(t\text{-}1)_{it} + \beta_3 gds(t\text{-}1)_{it} + \beta_4 fs_{it} + \beta_5 fcf_{it} + \beta_6 roa_{it} + \beta_7\ FL_{it} + \beta_8 BI_{it} + \beta_9\ BS_{it} + \mu_i + \varepsilon_{it} \quad (2)$$

For the analysis of data, a few statistical tools have been used such as Microsoft Excel and Stata SE14.1.

## Results and Analysis

**Descriptive Analysis**

Table 2 provides descriptive statistics for dependent, independent, and control variables. As can be observed from the table, the average dividend payout ratio is 28.87, indicating that, on average, companies distribute approximately 28.85% of their earnings as dividends. However, considerable variation (standard deviation = 33.75) suggests that dividend policies vary widely among the companies in the panel. The combined ESG score's mean value is 35.13639, compared to 16.7996 for environmental, 20.62578 for social, and 76.31547 for governance disclosure. It is further noted that the mean value of the governance component is significantly higher than the other two components, suggesting that the Indian companies in the sample place greater emphasis on compliance. This reflects the stronger adherence of Indian firms to corporate governance mechanisms, indicating a more robust focus on governance practices.

Coming to the control variable roa with a mean of 8.89, means profitability, with a significant SD of 8.19, showing variations in asset efficiency among firms. Financial leverage with a mean value of 2.48, has a high SD of 1.91, indicating variability in the debt levels among firms.

**Table 2: Descriptive Statistics**

| Variables | Mean | Std Dev | Min | Max |
|---|---|---|---|---|
| dpr | 28.87025 | 33.75341 | 0 | 235.898 |
| L.esgds | 35.13639 | 14.92242 | 2.361 | 76.889 |
| L.eds | 16.7996 | 18.55981 | .3322 | 73.875 |
| L.sds | 20.62578 | 12.5233 | .4534 | 69.8912 |
| L.gds | 76.31547 | 12.62854 | 5.4816 | 98.6153 |
| fs | 10.92503 | .6611571 | 8.862432 | 13.17599 |
| fcf | 22.21148 | 1.727222 | 16.32511 | 26.74203 |
| roa | 8.885031 | 8.193467 | 32.3587 | 95.1795 |
| bi | 50.84676 | 10.8529 | 0 | 100 |
| fl | 2.477514 | 1.908624 | 1.0507 | 40.7612 |
| bs | 9.831746 | 2.435053 | 2 | 22 |

Source: Author's calculation

**Multicollinearity**

**Table 3: VIF Multicollinearity Result for Model 1**

| VARIABLE | VIF | 1/VIF |
|---|---|---|
| fs | 3.43 | 0.269618 |
| fcf | 2.64 | 0.347546 |
| L.esgds | 1.59 | 0.643598 |
| roa | 1.28 | 0.764070 |
| bs | 1.12 | 0.892377 |
| fl | 1.10 | 0.901350 |
| bi | 1.03 | 0.963181 |
| MEAN VIF | 1.74 | |

Source: Author's calculation

Table 3 and Table 4 provide VIF results for all variables in both the models respectively. The VIF is a measure of multicollinearity that indicates how much a variable is associated with the model's other independent variables. None of the VIF scores were found to be above 5.0 and have therefore been deemed satisfied, which is per Woolridge (2009) and Keller (2017). Since the VIF test did not indicate any severe signs of multicollinearity in both models, no multicollinearity issues were detected in the regression model.

**Table 4: VIF Multicollinearity Result for Model 2**

| VARIABLE | VIF | 1/VIF |
|---|---|---|
| fs | 3.44 | 0.269664 |
| fcf | 2.64 | 0.346812 |
| L.sds | 2.71 | 0.362301 |
| L.eds | 2.53 | 0.377613 |
| L.gds | 1.36 | 0.697112 |
| roa | 1.28 | 0.763822 |
| bs | 1.12 | 0.889164 |
| fl | 1.10 | 0.900969 |
| bi | 1.10 | 0.908078 |
| MEAN VIF | 1.92 | |

Source: Author's calculation

**Panel Data Regression Analysis**

Given the endogeneity concerns commonly associated with dividend policies, a dynamic panel Generalized Method of Moments (GMM) approach is employed to control for potential biases and ensure robust estimation. The results show that the lagged value of dpr is significantly positive in both models. This persistence suggests that past dividend decisions exert a positive and significant impact on current payout decisions. This phenomenon aligns with the theory of dividend smoothing (Lintner, 1956), where firms adjust dividend payments gradually in response to past dividends rather than drastic changes, reflecting a cautious approach to payout adjustments. Table 5 demonstrates the results of our regression models.

**The ESG Score and the Dividend Payout**.

The aggregate ESG score (esgds) is positively related to dividend payout, suggesting a cumulative effect where holistic ESG practices foster stakeholder trust, reduce perceived risk and support higher dividend levels. This echoes findings by Benelemih (2017), Jauberti et al. (2020), and Ni & Zhang (2021), who emphasize the integral role of ESG practices in shaping investor expectations and dividend policies.

Using lagged ESG variables implies that the study examines how ESG disclosures from past periods affect current dividend payouts. The lag captures the delayed impact of a firm's previous ESG activities, reflecting how decisions on dividends might depend on prior strategic choices or disclosures. Positive disclosures may build trust over time, leading firms to issue dividends as a means of rewarding loyal investors. A firm's strategic planning, influenced by its ESG policies, may lead to increased profits or surplus cash flow over time, enabling dividend payouts in subsequent periods. Firms with consistent ESG practices may be viewed as more resilient, financially sound, and future-oriented. As they maintain investor confidence, they may feel pressure to pay dividends to sustain this positive relationship.

We have identified the impact of current and previous year performance on operating market, and financial performance in the industrial sector. The results are found to be significant for operating and market performance. In the case of lagged ESG performance, we have identified the impact on the current year's financial performance. The results are consistent in the case of current as well as lagged performance.

**The ESG Dimensions and the Dividend Payout**

The findings regarding ESG disclosure scores, specifically the Environmental Disclosure Score (eds) and Governance Disclosure Score (gds), reveal significant positive lagged effects on dpr. This relationship suggests that firms with strong ESG practices, particularly in environmental and governance domains, have more flexibility and investor trust to issue dividends. This is consistent with the stakeholder theory, where robust ESG performance mitigates agency problems, aligns management with shareholder interests, and enables higher dividend payouts. The positive link between past environmental disclosure and current dividend payouts aligns with recent findings by Benlemlih (2019), who suggests that environmental responsibility enhances firm reputation and investor confidence, thereby enabling sustainable dividend distributions. Similarly, Ni and Zhang (2021) find that environmental initiatives can foster long-term financial benefits, such as cost efficiencies, which can free up resources for dividends. The significant influence of governance disclosures on dividends is consistent with the work of Samet (2020), which argues that firms with strong governance practices reduce agency conflicts and increase transparency, reassuring shareholders about management's commitment to fair and stable returns. Jung and Kim (2022) also found that governance factors improve dividend policies by reducing information asymmetry, enabling firms to consistently meet dividend expectations. The Social Disclosure Score (sds**)**, while included, does not show a statistically significant effect, which may indicate that investors view social initiatives as less directly tied to immediate financial performance or liquidity, unlike environmental and governance factors which may have more direct operational impacts (Cheung, Samet, & Cespedes, 2021). This finding suggests that, social initiatives are not capitalized into dividend expectation in the short term by investors which highlights the priority of the Indian invetsors.

The analysis also includes several control variables to account for the influence of financial and corporate factors on dividend payout policies. These control variables show results consistent with previous research, further validating their inclusion.

Return on assets has a positive and significant relationship across both models suggesting that more profitable firms distribute higher dividends. This finding aligns with the residual theory of dividends (Fama & French, 2001), where firms with high profitability can afford greater payouts. Benlemlih (2019) also highlights that profitability is directly tied to the financial health of firms, which drives stable and predictable dividend payments. The negative coefficient on board independence implies that firms with more independent boards may adopt conservative dividend policies. Firm size shows a significant negative relationship with dividend payouts. Larger firms may have more substantial reinvestment opportunities or expansion goals, which reduces the cash available for dividends. Studies by Cheung et al. (2021) support this, suggesting that larger firms retain earnings for competitive positioning and long-term projects rather than paying them out. Free cash flow positively influences DPR, indicating that organisation with higher free cash flows tend to issue dividends. This finding aligns with Jensen's (1986) Free Cash Flow Hypothesis, where surplus cash is distributed to avoid inefficiencies associated with retaining excess funds. Benlemlih (2019) also suggests that firms with higher free cash flows can issue dividends without jeopardizing operations. Financial leverage (FL) negatively impacts DPR, consistent with studies by Samet et al. (2020), which argue that leveraged firms often retain earnings to meet debt obligations and reduce financial risk. Board size does not show a statistically significant relationship with DPR. This lack of significance may suggest that dividend policies are more influenced by the composition (e.g., independence) than the size of the board, which is consistent with findings from Jung and Kim (2022), who argue that board characteristics are nuanced in their impact on financial policies.

**Diagnostic Tests and Model Validity**

The significant Arellano-bond AR(1) result and non-significant AR(2) result satisfy the GMM assumption of no second-order serial correlation, supporting the use of lagged instruments (Arellano & Bond, 1991). The non-significant p-values from the Sargan (p = 0.824) and Hansen (p = 0.666) tests indicate the instruments' validity, affirming that the model is not over-identified. Roodman (2009) highlights that these tests are crucial for verifying instrument exogeneity, and the results align with this criterion, bolstering the reliability of the estimates. The difference-in-Hansen test results affirm the exogeneity of the instrument subsets, with non-significant p-values suggesting that the selected instruments are appropriate for this model.

**Table 5: GMM results for both models**

| | (1) | (2) |
|---|---|---|
| VARIABLES | dpr | dpr |
| L.dpr | 0.188*** | 0.191*** |
| | (0.0710) | (0.0702) |
| L.eds | | 0.388** |
| | | (0.179) |
| L.sds | | -0.114 |
| | | (0.223) |
| L.gds | | 0.580** |
| | | (0.274) |
| roa | 0.406** | 0.416** |
| | (0.327) | (0.330) |
| bi | -0.297*** | -0.367*** |
| | (0.0932) | (0.104) |
| Fs | -7.591** | -8.373** |
| | (5.221) | (5.122) |
| fcf | 2.253** | 2.248** |
| | (0.995) | (0.983) |
| Fl | -0.765** | -0.735** |
| | (0.345) | (0.344) |
| bs | 0.271 | 0.360 |
| | (0.481) | (0.490) |
| L.esgds | 0.649** | |
| | (0.265) | |
| Constant | 45.28 | 32.51 |
| | (41.56) | (44.74) |
| Observations | 1,225 | 1,222 |
| Number of Id | 249 | 249 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Result obtained from Stata

## Robustness Check

Replacing the dividend payout ratio by dividend per share, the relationship among the lagged ESG scores on dividends is still significant and positive, which highlights that the ESG disclosure scores have a stable effect on the dividend policies of Indian companies as shown in Table 6. Coming to the control variable they are showing the same results as well making the results consistent.

**Table 6: GMM results for alternative dividend measure**

| VARIABLES | (1) dps | (2) dps |
|---|---|---|
| L.dps | 0.734*** | 0.743*** |
| | (0.0896) | (0.0891) |
| L.eds | | 0.0391** |
| | | (0.0759) |
| L.sds | | -0.0338 |
| | | (0.0786) |
| L.gds | | 0.354*** |
| | | (0.130) |
| roa | 0.537*** | 0.544*** |
| | (0.150) | (0.150) |
| bi | -0.0783 | -0.104* |
| | (0.0550) | (0.0595) |
| Fs | -3.348** | -1.500** |
| | (2.490) | (2.150) |
| fcf | 0.553** | 0.651** |
| | (0.399) | (0.406) |
| fl | 0.224** | 0.124** |
| | (0.168) | (0.135) |
| bs | -0.119 | -0.0506 |
| | (0.240) | (0.234) |
| L.esgds | 0.357** | |
| | (0.148) | |
| Constant | 14.78 | -20.71 |
| | (19.00) | (16.60) |
| Observations | 1,224 | 1,221 |
| Number of id | 249 | 249 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Results obtained from Stata

## Conclusion

This study aims to measure the effect of corporate sustainability in terms of ESG measured by Bloomberg Disclosure Score on company dividend decisions. The data used were mostly obtained from the Bloomberg Database for the period 2014 to 2022. There are 231 companies and 2079 firm-year observations in the final sample. The independent variables of the study are combined ESG Scores and individual components i.e. E, S, G, and the dividend policy is the dependent variable, measured by the its payout ratio.

This study reveals that the combined ESG disclosure score, along with its environmental and governance components, exerts a significant positive influence on dividend payout ratios. In contrast, social disclosure scores do not demonstrate a statistically significant relationship with dividends. This discrepancy may stem from the distinctive nature of social initiatives, which often require longer timelines to generate visible financial returns. Social disclosures typically center on broader stakeholder engagement and community-oriented efforts, which may not immediately translate into a company's short-term financial metrics. These finding highlights that, while environmental and governance disclosures are more directly linked to near-term financial results, social disclosures may need a longer period to deliver measurable financial impacts.

Additionally, ESG factors' positive effects on dividends appear to be time-lagged, suggesting that the benefits of ESG commitments emerge gradually. The delayed results highlight that firms who follow strong ESG practices can realize cumulative benefits as these practices become deeply embedded within their strategy, ultimately fostering financial stability and enhancing shareholder returns. This outcome aligns with recent studies that emphasize the gradual value appreciation of ESG adoption, confirming that dividends linked to ESG commitments accrue progressively as firms continue to prioritize sustainability.

The findings support both agency theory and signalling theory within the ESG-dividend context. From an agency theory perspective, increased transparency through ESG disclosures helps reduce information asymmetry and align managerial actions with shareholder interests, fostering higher dividend distributions. ESG reporting can address potential agency conflicts, reinforcing governance and accountability commitments, strengthening investor trust and increasing shareholder returns.

Signalling theory also explains these results effectively. Companies engaging in robust ESG reporting send a positive signal to the market, reflecting strong governance practices and responsible management. Such disclosures serve as credible signals of the firm's long-term viability and strategic resilience, building investor confidence and enabling firms to sustain more substantial dividend policies. The findings echo the seminal work of Cheung (2018), and Ni and Zhang (2021), who underscore the importance of ESG in signalling transparency and corporate commitment to ethical practices, thereby enhancing market valuation and promoting stable dividend policies.

In conclusion, this study enriches the body of literature on ESG and financial performance by presenting empirical evidence of the strategic value of ESG initiatives in supporting dividend policies, particularly within the context of emerging markets like India. By empirically affirming agency and signaling theories in an ESG context, it underscores the pivotal role of environmental and governance disclosures in driving sustainable corporate growth and highlights the importance of recognizing ESG's lagged effects on dividend policies. These insights are essential for investors, policymakers, and corporate leaders as they navigate the dynamic landscape of responsible investing and work toward integrating sustainability within corporate financial strategies. Investors should consider including ESG elements as it can give a more thorough assessment of a company's long-term viability. ESG reporting should be open and credible, and policymakers should aim towards it. Improving the quality and consistency of ESG disclosure ratings can allow for more relevant analysis and decision-making.

## Limitations of the Study

This study is not free from limitations. Firstly, the dividend policy is measured by the dividend payout ratio only, ignoring the other measures such as dividend yield, etc. Secondly, the study is based on secondary data, which inherently possesses the possibility of human error.

Additionally, the study limits till 2022, post which various other changes in the ESG landscape has been seen. Furthermore, this study shows the sample selection bias by excluding firm who did not declare any dividends.

## Scope for Future Research

The current study has focused on the broad ESG dimensions and their individual components without delving into more subdimensions within each. The future studies can explore factors, like “the carbon emission”, “management”, and “corporate mechanism”, to get a better link between ESG and the dividend policy. Furthermore, industry-specific analysis can be done to understand the relevance of ESG practices as they vary due to different regulations, capital involvement, and stakeholder pressure. Future researchers can draw out more comparative results between the Indian market and other developed or developing markets.

Notes

1. “Available at: https://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf”
2. “Available at: SEBI_Circ_13082012_3.pdf”
3. “Available at: SEBI/HO/CFD/CMD-2/P/CIR/2021/562”
4. “Available at: https://insights.issgovernance.com/posts/budget-bugle-2023-india-through-the-environmental-and-social-lens/”

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## ANNEXURE

**Table 1: Variables**

| SYMBOL | VARIABLES | | SOURCE |
|---|---|---|---|
| esgds | ESG Disclosure score | Independent Variable | Bloomberg |
| eds | Environmental Disclosure Score | Independent Variable | Bloomberg |
| sds | Social Disclosure Score | Independent Variable | Bloomberg |
| gds | Governance Disclosure Score | Independent Variable | Bloomberg |
| dpr | Dividend Payout Ratio | Dependent Variable | Bloomberg |
| fs | Firm Size | Control Variable | Bloomberg |
| bs | Board Size | Control Variable | Bloomberg |
| roa | Return on Assets | Control Variable | Bloomberg |
| fl | Financial Leverage | Control Variable | Bloomberg |
| bi | Board Independence | Control Variable | Bloomberg |
| fcf | Free cash flow | Control Variable | Bloomberg |

Source: Author's calculation

**Table 2: Descriptive Statistics**

| Variables | Mean | Std Dev | Min | Max |
|---|---|---|---|---|
| dpr | 28.87025 | 33.75341 | 0 | 235.898 |
| L.esgds | 35.13639 | 14.92242 | 2.361 | 76.889 |
| L.eds | 16.7996 | 18.55981 | .3322 | 73.875 |
| L.sds | 20.62578 | 12.5233 | .4534 | 69.8912 |
| L.gds | 76.31547 | 12.62854 | 5.4816 | 98.6153 |
| fs | 10.92503 | .6611571 | 8.862432 | 13.17599 |
| logfcf | 22.21148 | 1.727222 | 16.32511 | 26.74203 |
| roa | 8.885031 | 8.193467 | 32.3587 | 95.1795 |
| bi | 50.84676 | 10.8529 | 0 | 100 |
| fl | 2.477514 | 1.908624 | 1.0507 | 40.7612 |
| bs | 9.831746 | 2.435053 | 2 | 22 |

Source: Author's calculation

**Table 3: VIF Multicollinearity Result for Model 1**

| VARIABLE | VIF | 1/VIF |
|---|---|---|
| fs | 3.43 | 0.269618 |
| logfcf | 2.64 | 0.347546 |
| L.esgds | 1.59 | 0.643598 |
| roa | 1.28 | 0.764070 |
| bs | 1.12 | 0.892377 |
| fl | 1.10 | 0.901350 |
| bi | 1.03 | 0.963181 |
| MEAN VIF | 1.74 | |

Source: Author's calculation

**Table 4: VIF Multicollinearity Result for Model 2**

| VARIABLE | VIF | 1/VIF |
|---|---|---|
| fs | 3.44 | 0.269664 |
| logfcf | 2.64 | 0.346812 |
| L.sds | 2.71 | 0.362301 |
| L.eds | 2.53 | 0.377613 |
| L.gds | 1.36 | 0.697112 |
| roa | 1.28 | 0.763822 |
| bs | 1.12 | 0.889164 |
| fl | 1.10 | 0.900969 |
| bi | 1.10 | 0.908078 |
| MEAN VIF | 1.92 | |

Source: Author's calculation

**Table 5: GMM results for both models**

| VARIABLES | (1) dpr | (2) dpr |
|---|---|---|
| L.dpr | 0.188*** | 0.191*** |
| | (0.0710) | (0.0702) |
| L.eds | | 0.388** |
| | | (0.179) |
| L.sds | | -0.114 |
| | | (0.223) |
| L.gds | | 0.580** |
| | | (0.274) |
| roa | 0.406** | 0.416** |
| | (0.327) | (0.330) |
| bi | -0.297*** | -0.367*** |
| | (0.0932) | (0.104) |
| Fs | -7.591** | -8.373** |
| | (5.221) | (5.122) |
| logfcf | 2.253** | 2.248** |
| | (0.995) | (0.983) |
| Fl | -0.765** | -0.735** |
| | (0.345) | (0.344) |
| bs | 0.271 | 0.360 |
| | (0.481) | (0.490) |
| L.esgds | 0.649** | |
| | (0.265) | |
| Constant | 45.28 | 32.51 |
| | (41.56) | (44.74) |
| Observations | 1,225 | 1,222 |
| Number of Id | 249 | 249 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Result obtained from Stata

**Table 6: GMM results for alternative dividend measure**

| VARIABLES | (1)<br>dps | (2)<br>dps |
|---|---|---|
| L.dps | 0.734*** | 0.743*** |
| | (0.0896) | (0.0891) |
| L.eds | | 0.0391** |
| | | (0.0759) |
| L.sds | | -0.0338 |
| | | (0.0786) |
| L.gds | | 0.354*** |
| | | (0.130) |
| roa | 0.537*** | 0.544*** |
| | (0.150) | (0.150) |
| bi | -0.0783 | -0.104* |
| | (0.0550) | (0.0595) |
| Fs | -3.348** | -1.500** |
| | (2.490) | (2.150) |
| logfcf | 0.553** | 0.651** |
| | (0.399) | (0.406) |
| fl | 0.224** | 0.124** |
| | (0.168) | (0.135) |
| bs | -0.119 | -0.0506 |
| | (0.240) | (0.234) |
| L.esgds | 0.357** | |
| | (0.148) | |
| Constant | 14.78 | -20.71 |
| | (19.00) | (16.60) |
| Observations | 1,224 | 1,221 |
| Number of id | 249 | 249 |

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Results obtained from Stata

# A Study of Human Resource Development Practices and Organizational Outcomes with Reference to JS in Banking Sector

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## Abstract

Every organization has its own ways to manage and develop human resources in their organizations. HRD practices prevailing in an organization can express the effectiveness of the organization and its impact on overall organizational performance. The present research tried to identify the principal practices of HRD in the Indian banking sector and further to see that how these practices are impacting the productivity of the organization as well as affecting the satisfaction level of the employees with the help of JS. To conduct the statistical analysis a questionnaire was circulated amongst 500+ professionals, they are target respondents as per the objectives of the research. Finally, 400 responses of target employees were taken from the different public and private sector banks (Delhi/NCR) for data analysis. Multiple regression analysis was used to determine the contribution of eight HRD Mechanisms toward influencing JS. The study highlights that the HRD mechanism and organizational practices have a positive impact on the JS and performance of the employees. Our results are exhibiting that HRD practices have a positive impact on organizational performance and JS. The study provides useful implications for managers, banking institutions, and policymakers to enhance the productivity of the workforce and the profitability of the organization.

**Keywords:** Organizational Performance (OP), Job Satisfaction (JS), HRD Practices, Indian Banking Sector, Regression Analysis

## Introduction

The world does not remain the same rather than it keeps on changing now and then. Moreover, on daily basis, there is new development happening in the field of technology, process involvement, new idea generation, and business environment. Human asset is the best investment and the production factor in the long-run economy, improved productivity, and organizational performance (Nafukho, Hairston, & Brooks, 2004; Akinyemi, Abiddin, & Malaysia, 2013; Gidado, Kusairi, & Muhamad, 2014; Bawono, S., 2021). HRD (HRD) is gaining more importance every day and becoming strategically important for professional practices and academic studies.

This is because, in the past few decades, HRD gained its value and relevance in the area of management development owing to a high degree of competition and changes in the business environment and it is a key factor to gain a competitive advantage over the competitors (Barney, & Wright, 1998; Wright, & Boswell, 2002; Luthans, & Youssef, 2004). Despite the fact and significance of HRD, there is a dearth existing in this specific area, especially empirical researches are very less, (Paul, & Anantharaman, 2003; Holton III, & Yamkovenko, 2008; Akdere, & Egan, 2020) suggested that HRD–OP paradigm has still existed and unexplored which focused upon the productive measures of the HRD and OP.

Further, HRD is an area that constantly thriving researchers, academicians, and practitioners to conduct research gains but hardly due weightage has been given to the banking employees with special reference to India. A satisfied employee always tries to give more effort, feels better in the company, performs, and feels safe (Wolniak and Olkiewicz, 2019). This study is being conducted by identifying the gaps on based upon the review of literature and particular research problems as identified in the study of Alagraja (2013). The study utilized concretely utilize the existing literature on the topic to identify research gap that exists in the HRD-OP linkage research in the recent past. In addition to this, the current study also tries to add more value to HRD practices and how these mechanisms are helping the organization to gain a situation which allows the company to produce more with satisfied employees and achieve organizational effectiveness.

In totality, this research makes an attempt the add following contributions to HRD literature. Firstly, we develop a systematic knowledge of the concepts and relationship among them that could be model to establish some empirical relationship between HRD mechanisms and OP and JS. Secondly, Confirmatory Factor Analysis CFA technique has been used to develop some constructs for HRD mechanisms to apply regression between JS (dependent variable) with HRD mechanism construct (independent variables). Previous studies have mentioned that these studies have given conceptualize and test different dimensions of HRD under the same name, which resulting in mixed empirical findings and controversy on the dependency of HRD in performance (Tharenou et al., 2007). For instance, HRD focusing on quantitative dimensions, such as the Training & Development, Quality of Work Life, and Role Analysis & Development on HRD activities.

## Literature Review

The research on HRD and Organizational practices has explored by many researcher and proposed diverse findings and the prominent conclusion of the topic supported the view that there is a coherence between HRD Practices and Organizational performance measures which also highlights JS. HRD practices are helping the organization to achieve its goal and HRD professionals help the employees to nurture their potential and to perform their future roles (Lengnick-Hall, & Lengnick-Hall, 2003; Gidado, Kusairi, & Muhamad, 2014; Maheshwari, et. al., 2017; Jeong and Park 2020; Bawono, S., 2021). HRD means identifying the future potential and to provide help in identifying successor managers to perform the future role required by the organization.

The idea of HRD has developed alike a tactic tool to progress the skills and competencies of the existing workforce to have the advantage of competitiveness (Barney, & Wright, 1998; Wright, & Boswell, 2002; Luthans, & Youssef, 2004), well proved by them in their studies. The literature has proved that (Swanson & Holton, 2009; Almatrooshi, Singh, & Farouk, 2016; Forés,

& Camisón, 2016) organizational success depends upon the talent, inteliigence and experienceskills, knowledge, and experience of its employees. Further the studies of Festing, & Schäfer (2014); Choudhary (2016); Hongal & Kinange (2020) highlighted a prominent problem of retention of talent which is an even bigger challenge for the organizations in the current time. Consequently, the cutthroat competition has also increased which poses many opportunities for the employee. Therefore, providing good career goals with prospective growth not only for an individual but the organizations as well can help the organizations retain the best talent with them (Cappelli, 2000; Porter, 2011; Festing & Schäfer, 2014; Choudhary, 2016; Keller & Meaney, 2017). JS and motivation are again imperative constituents of organizational performance and have effect on the financial presentation of the organization, more particularly strategically important in the banking industry that led to the efficiency and effectiveness of the banking system and also the whole financial system.

HRD Practices are having a positive correlation on JS (Koley, J. Tidke and Joshi, C. and Khan, 2025) and helps in building the positive attitude of the employees towards the organization and their work.

Parek k 2022 and 2024 research says that innovative HRD Practices are helpful in building competitive advantage over the other organization. It shows that there is always a positive coherence between the HRD Practices and JS and enhancing the productivity and efficiency of the employees which leads to the enhancement of organizational Performance.

Training and development (T&D) programs are a crucial element of HRD practices in the organization, (Anis, Nasir, & Safwan, 2011; Mapelu, & Jumah, 2013; Aleem, & Bowra, 2020) have proved in their studies that these programs reduce employee turnover in the organization. They also talked about the integration of strategic Human Resource policies and practices has a great impact on employees' performance. In continuation of this many researchers Katou, & Budhwar, (2012); Agwu, & Ogiriki, (2014); Ciobanu, Androniceanu, & Lazaroiu, (2019) suggested that HRD system matrix have a positive effect on employee motivation/commitment and organizational performance. Research also examined that there is a good influence of HRD Practices and it is increasing the overall productivity of the employees and increasing organizational effectiveness in the service sector (Gould-Williams, J., 2003; Chand, & Katou, 2007; Galperin, & Lituchy, 2014; Otoo, et. al., 2019).

Human resource literature argued and explained that there are multiple dimensions of HRD and these are directly or indirectly affecting organizational performance Shung, & Choi, (2014); Agwu, & Ogiriki, (2014); Ciobanu, Androniceanu, & Lazaroiu, (2019), they examined the manufacturing companies and explored that there is a positiveeffect of HRD practices and it develops worker competencies and hence increases productivity which is the financial outcome of the organization. (Heraty, & Morley, 1995; Maxwell, & Watson, 2006; Prayag, & Hosnay, 2015), revealed that in the hotel industry, HRD practices have increased the operational efficiency of the line managers.

The HRD interventions show that there is a significant affect of selected HRD interventions on organizational effectiveness (Potnuru, & Sahoo, 2016; Kareem, M. A., 2019), and selected HRD interventions have increased employee competencies. Sanchez et.al. (2017), identifies that a high intensity of HR formalization has a positive impact on organization ability and performance. HRD practices have an impact on employees' intentions to check this proposition, (Juhdi, Pa'wan, & Hansaram, 2013; Kundu, & Gahlawat, 2015; Uraon, 2018), concludes that HRD customs have a positive impact on employee intentions to stay in the firm as well as on the three components of organizational commitment. The study further identified that a perceptual and rugular commitment positively affected employees' intention to stay.

In the HRM JS is a critical matter of research from past time, it motivated researchers to test the impacts of HRD on JS. This phenomenon is being tested by Lim (2010); Solkhe & Chaudhary (2011); Gopinath, & Shibu (2014), and their findings revealed that there is a impactful relationship between HRD operation and JS. Gopinath & Shibu (2014) conducted their study on BSNL employees and found that there is a impactful cohesiveness between HRD Practices and JS and this is positively associated with organizational performance. HRD practices in the banking sector can affect JS, (Dirani, K. M., 2009; Jegan, & Gnanadhas, 2011, Saravani, & Abbasi, 2013; Gupta, el. al., 2019) attempt to check this hypothesis and found that HRD practices have a strong influence on banking sector employees', work culture, their productivity, and in totality impacts jab satisfaction. The study has been conducted through in-depth interviews and revealed that HRD is related to improvements in knowledge sharing and contributing to organizational success. With the help of this resaerchers formulated the following objectives:

- To identify the employee perceptions towards HRD mechanisms in selected banks
- To identify the relationship between HRD mechanisms and JS (taken as perceptual measure of organizational Performance) in the selected sector.
- To identify the impact of HRD Mechanisms on JS in the selected sector.

According to the above objectives, following hypotheses are drawn.

**H01**: There are no significant differences of employee perception exist between the selected public and private sector banks under study on account of HRD and its mechanisms.

**H02(a)**: There is no impactful relationship among HRD Mechanisms and JS.

**H02(b)** There is no impact of HRD mechanisms on JS among selected banks in this research.

## Methodology

The current study is based on a quantitative design. A quantitative design is always suitable for testing of hypothesis which provides the relationship between the independent variable and dependent variable (Sekram & Bougie, 2013). The main objective of this quantitative design study is to determine the significance effect of HRD mechanisms i.e; Training and Development (Al-Ali, A. A., 2011; Rowland, Hall, & Altarawneh, 2017; Garavan, et, al; 2019; Otoo, et. al; 2019), Performance Appraisal (Adhikari, 2010; Otoo, & Mishra, 2018; Otoo, et. al; 2019), Career Planning Development (Adekola, B., 2011; Otoo, F. N. K., 2019; Otoo, et. al; 2019), Employee involvement and Empowerment (Alagaraja, & Egan, 2013; Jose, & Mampilly, 2014; Rumman, Al-Abbadi, & Alshawabkeh, 2020), Compensation & Reward System (Allui, & Sahni, 2016; Otoo, & Mishra, 2018; Gope, Elia, & Passiante, 2018), Quality of Work Life (Vagharseyyedin, Vanaki, & Mohammadi, 2011; Farid, et al., 2015), Role Analysis Development, and Organizational Culture on organizational performance (Chang, & Lee, 2007; Aboramadan, et al., 2020), further how it influences the JS level of the employees in the Indian Banking Sector. Here, in current study the proposed framework is developed for this research, it is showing in Figure 2.

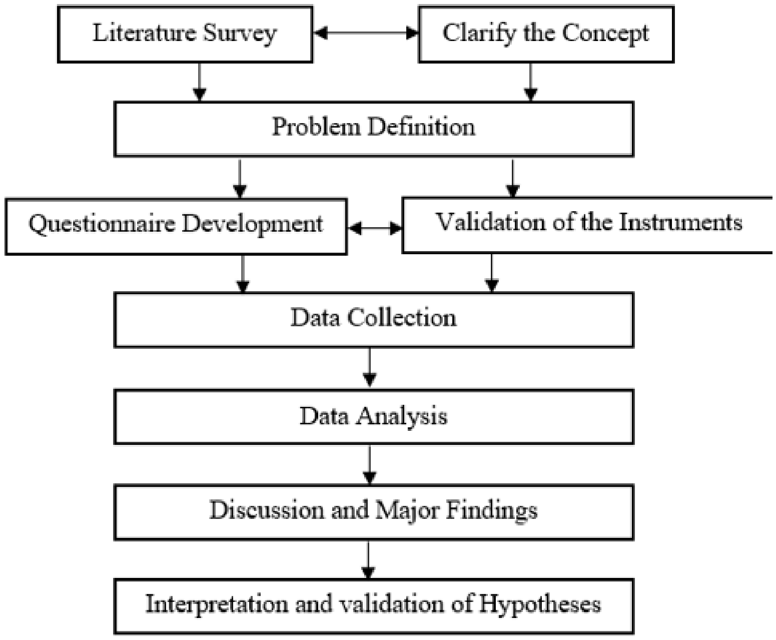


**Figure 1: Proposed Framework of the study**

The questionnaire is the most commonly utilized tool to gather the information in the survey method. The questionnaire was requested to fill up by the employees (Executive and managerial level) of public and private sector bank branches all across Delhi-NCR. Samples have been selected through convenience and judgmental sampling. The questionnaire was circulated among 500 employees and researcher received only 400 complete questionnaires after completing the whole process of sample collection.

Next, the most important aspect of the research is/are to use effective tools to analyze the data and interpret the result. Data analysis was identified to direct the research problem by using Statistical Package for Social Science (SPSS) and the Analyses of Moment Structure (AMOS). Confirmatory Factor Analysis (CFA) has been used to assess the validity and reliability of the items used in the questionnaire by using convergent and discriminate validity. The overall model fit was evaluated by using seven goodness-of-fit indices. In addition, Partial least squares structural equation modeling (SEM) was identified to test facts about the proposed hypotheses. Multiple regression techniques are applied to identify the cohesiveness among dependent and independent variables.

The regression equation of JS from the 8 HRD Mechanisms as perceived by the banking professionals is:

$$\boldsymbol{Y = \alpha + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5 + \beta 6X6 + \beta 7X7 + \beta 8X8 + \varepsilon} \qquad (1)$$

Where Y is the dependent variable and represents JS, α is constant, X1=Training & Development, X2=Potential Appraisal, X3=Career Planning & Development, X4=Compensation & Reward System, X5=Employee Involvement & Empowerment, X6=Quality of Work Life, X7=Role Analysis & Development, and X8=Organisational Culture, (β1, β2, β3, β4, β5, β6, β7, and β8) are the coefficients of respective variables.

‘Reliability’ is being defined the consistency of the variable which is intended to measure. In the present research, the reliability of the HRD Survey and JS was ascertained through Cronbach alpha coefficient as shown in Table 3.1. The reliability coefficient indicated that the HRD Survey used for measuring perceptions towards HRD Mechanisms is quite reliable as the alpha value was 0.955. The Reliability Coefficient of the JS Scale was 0.853 (As per appendix: 2).

As the value exceeded the minimum requirement, it is thereby demonstrated that all the factors of the HRD Survey and JS Scale were internally consistent.

**Table 1: Reliability of the Instruments Used**

| | HRD Survey (Self-Constructed) | JS Scale (Brayfield and Rothe, 1951) |
|---|---|---|
| **Number of items in beginning** | 89 | 5 |
| **No of Items after Pilot Study** | 75 | 5 |
| **No of Items after CFA** | 50 | 4 |
| **Cronbach Alpha** | **.955** | **0.853** |

*Note: * Values of 0.60 and closer to 0.90 testify strong reliability of the scale.*

Subsequently, Confirmatory Factor Analysis (CFA) technique was applied. Cronbach Alpha of the HRD survey items is coming out 0.95. On the other hand, JS scale Cronbach Alpha is again over and above 0.6 (i.e., 0.853), here also items are reliable on the basis of Cronbach Alpha parameter. Both category of instruments are showing strong reliability as value is either closer to 0.9 or above.

**Table 2: Assessment of KMO & Bartlett's Test**

| **KMO and Bartlett's Test** | | |
|---|---|---|
| **Kaiser-Meyer-Olkin Measure of Sampling Adequacy.** | | ***.776*** |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 44584.996 |
| | Df | 1953 |
| | Sig. | 0.000 |

Source: Compiled and calculated through the questionnaire.

Here in the Table 2, results of the KMO Test are plotted, KMO value is 0.776 which is higher than the standard criteria of 0.5 or 0.6; therefore, it indicates that the information gathered is good for factor analysis. In addition, the Bartlett's Test of Sphericity results are also statistically significant.

## Results

The present study provides the results obtained from Confirmatory Factor Analysis using AMOS Software (Analysis of Moment Structures) for determining and confirming the factors of the HRD Index. Here CFA has also been used to assess the quality of measures as well as review the suitability of the Questionnaire, followed by multiple regressions in the later part of the analysis. (Lin, 2008; Qiu and Lin, 2009). In the very first step, research described the individual construct and then tested the construct through CFA and omitted those whose value came below 0.70 because the constructs were not explaining much about the variables.

**Table 3: Summary Statistics of HRD Index & HRD Mechanisms after CFA**

| Constructs | Sr. No. | Indicators | Loading | Mean | Item to Total Correlation |
|---|---|---|---|---|---|
| Training & Development | 1 | TD3 | 0.74 | 3.9550 | .494 |
| | 2 | TD4 | 0.76 | 3,9400 | .528 |
| | 3 | TD5 | 0.86 | 3.9600 | .588 |
| | 4 | TD6 | 0.98 | 3.9825 | .607 |
| | 5 | TD7 | 0.96 | 3.9625 | .592 |
| | 6 | TD8 | 0.94 | 3.9475 | .631 |
| | 7 | TD9 | 0.71 | 3.9950 | .479 |
| Performance Appraisal | 8 | PA4 | 0.54 | 4.2000 | .368 |
| | 9 | PA5 | 0.85 | 4.3425 | .414 |
| | 10 | PA6 | 0.98 | 4.3850 | .466 |
| | 11 | PA7 | 0.95 | 4.3950 | .488 |
| | 12 | PA9 | 0.47 | 4.5500 | .270 |
| Carrer Planning Development | 13 | CPD3 | 0.61 | 3.8625 | .534 |
| | 14 | CPD4 | 0.72 | 3.8450 | .652 |
| | 15 | CPD5 | 0.73 | 3.8325 | .688 |
| | 16 | CPD6 | 0.86 | 3.7875 | .724 |
| | 17 | CPD7 | 1.02 | 3.8250 | .672 |
| | 18 | CPD8 | 0.94 | 3.8625 | .596 |
| | 19 | CPD9 | 0.92 | 3.8250 | .598 |
| Employee Involvement & Enpowerment | 20 | EIE2 | 0.86 | 3.7925 | .729 |
| | 21 | EIE3 | 0.92 | 3.7725 | .750 |
| | 22 | EIE4 | 0.99 | 3.8550 | .638 |
| | 23 | EIE5 | 0.94 | 3.8200 | .655 |
| | 24 | EIE6 | 0.85 | 3.8025 | .672 |
| | 25 | EIE7 | 0.82 | 3.7500 | .722 |
| | 26 | EIE8 | 0.76 | 3.7950 | .645 |
| Compensation Reward System | 27 | CRS5 | 0.62 | 3.9100 | .628 |
| | 28 | CRS6 | 0.86 | 3.8725 | .587 |
| | 29 | CRS7 | 0.95 | 3.8475 | .479 |
| | 30 | CRS8 | 0.97 | 3.8250 | .413 |
| | 31 | CRS9 | 0.83 | 3.8600 | .302 |
| | 32 | CRS10 | 0.84 | 3.7550 | .286 |
| | 33 | CRS11 | 0.71 | 3.6350 | .179 |
| Quality of Work Life | 34 | QWL1 | 0.82 | 3.9900 | .639 |
| | 35 | QWL2 | 0.88 | 3.9650 | .707 |
| | 36 | QWL3 | 1.03 | 3.8975 | .746 |
| | 37 | QWL4 | 0.92 | 3.8500 | .739 |
| | 38 | QWL5 | 0.83 | 3.9175 | .684 |
| | 39 | QWL6 | 0.59 | 3.8900 | .569 |

| Constructs | Sr. No. | Indicators | Loading | Mean | Item to Total Correlation |
|---|---|---|---|---|---|
| **Role Analysis Development** | 40 | RAD1 | 0.83 | 3.4675 | .630 |
| | 41 | RAD2 | 0.91 | 3.4725 | .535 |
| | 42 | RAD3 | 0.99 | 3.6175 | .621 |
| | 43 | RAD4 | 0.91 | 3.7600 | .628 |
| | 44 | RAD6 | 0.69 | 3.3600 | .499 |
| | 45 | RAD7 | 0.76 | 3.7750 | .581 |
| **Organizational Culture** | 46 | OC3 | 0.61 | 4.1950 | .386 |
| | 47 | OC5 | 0.77 | 4.2700 | .325 |
| | 48 | OC6 | 0.94 | 4.3575 | .278 |
| | 49 | OC7 | 1.00 | 4.4375 | .205 |
| | 50 | OC8 | 0.95 | 4.4350 | .183 |

Source: HRD survey

The summary statistics Table indicates factor loadings on all 50 items categorized into eight mechanisms of HRD. In this majority of the factor loadings are well above the threshold limit of .70 leaving a few exceptions. All the items to total correlation are well above the threshold value of .35 with a few exceptions. Therefore, no items have been dropped further. For assessing the Measurement model fitness for HRD Practices through Goodness-of-fit Indices. The results tell us the model fit indices of all the constructs namely Training and development, Performance Appraisal, Career Planning Development, Employee involvement and Empowerment, Compensation & Reward System, Quality of Work Life, Role Analysis Development and Organizational Culture.

It is interpreted that on account of selected Goodness of Fit Indices almost all selected 8 variables were well above the threshold values which clearly indicates that model is a good fit model in the context of Indian banking industry.

To further verify the model, construct validity of the measurement model has been checked using indices such as AVEs. MSV and ASV. The results show that the presents indices of reliability and construct validity of all the constructs. It is further concluded from the above table that all the eight constructs exceeded the recommended cut off level of reliability i.e.; 0.70 and AVEs for the eight constructs are comfortably above 0.50. It is also interpreted that discriminant validity is well supported as the AVE for each construct is greater than MSV and ASV of each construct.

Further in this the researcher defined and operationalized all the constructs related to JS with their respective manifest variables as per their nature. Present study statistics indicate factor loadings on all 5 items of JS as subjective measures of OP. Here the majority of the factor loadings are well above the threshold limit of .70 leaving a few exceptions. All the items to total correlation are well above the threshold value of .35 with a few exceptions. Therefore, no items have been dropped further.

**Table 4: Model Fit Indices**

| MODEL FIT INDICES | | | | | | |
|---|---|---|---|---|---|---|
| | GFI | CMIN/DF | CFI | SRMR | RMSEA | PClose |
| Recommended Value | Greater than .90 | Less than 5 | Greater than .90 | Less than .09 | Less than .05 | Greater than .05 |
| Training & Development | .989 | 1.667 | 0.998 | 0.015 | 0.041 | 0.618 |
| Performance Appraisal | .998 | 0.921 | 1.000 | 0.012 | .000 | 0.679 |
| Carrer Planning &Development | .990 | 2.377 | 0.998 | 0.009 | 0.059 | 0.307 |
| Employee Empowerment | .981 | 5.126 | 0.995 | 0.019 | 0.102 | 0.012 |
| Compensation &Reward System | .990 | 2.819 | 0.997 | 0.029 | 0.068 | 0.189 |
| Quality of Work Life | .988 | 2.998 | 0.97 | 0.025 | 0.071 | 0.169 |
| Role Analysis Development | 1.000 | 0.015 | 1.000 | 0.001 | .000 | 0.94 |
| Organizational Culture | .998 | 1.549 | 1.000 | 0.005 | 0.037 | 0.415 |

**Table 5: Statistics of JS after CFA**

| Constructs | Sr. No. | Indicators | Loading | Mean | Item to Total Correlation |
|---|---|---|---|---|---|
| JS | 1 | JS 1 | .67 | 3.23 | .696 |
| | 2 | JS 2 | .73 | 2.93 | .754 |
| | 3 | JS 3 | .73 | 2.81 | .701 |
| | 4 | JS 4 | .92 | 2.85 | .652 |

It is interpreted from the above that on account of selected Goodness of Fit Indices of all the factors of JS was well above the threshold values which clearly indicates that model is a good fit model in the context of Indian banking industry leaving aside few exceptions. The SRMR is slightly above the cut-off value.

**Table 6: Model Fit Indices**

| | MODEL FIT INDICES | | | | | |
|---|---|---|---|---|---|---|
| | GFI | CMIN/DF | CFI | SRMR | RMSEA | PClose |
| JS (JS) | .997 | 1.098 | 1.000 | .028 | .016 | .624 |

The present study indices of reliability and construct validity of the construct of Organizational performance, namely JS. It is further concluded from that the construct exceeded the recommended cut off level of reliability i.e., 0.70 and AVEs for the three constructs are comfortably above 0.50. It is also interpreted that discriminant validity is well supported as the AVE for each construct is greater than MSV and ASV of each construct.

To achieve the first objective HRD Index, ANOVA was performed, the calculated f-value and p-value have significant differences. The results reveal significant differences statistically in between the selected organizations both individually as well as sector wise.

In the light of these results, regarding Hypothesis 1, the researcher understands that bankers' perceptions on account of HRD Mechanisms are observed to be significantly different in between the selected banks understudy and this difference is not by sampling or by chance. Here the probability in case of overall HRD Index as well as in case of eight selected mechanisms was .000 which is less than 0.05 at 95% level of significance. Moreover, it was also observed that Public Sector banks are seen better in terms of their HRD orientations as compared to private sector banks understudy.

**Table 7**

| **Variables →** | T&D | | PA | | CPD | | EIE | | CRS | | QWL | | RAD | | OC | | Overall HRD Index | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Organisations↓** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** |
| **HDFC Bank** | 3.360 | .769 | 4.190 | .759 | 2.955 | .820 | 2.814 | .717 | 3.730 | .820 | 3.398 | .778 | 3.155 | 1.103 | 4.018 | .970 | 3.4424 | .40600 |
| **ICICI Bank** | **4.187** | **.695** | 4.410 | .680 | 4.035 | .826 | 4.032 | .798 | 3.970 | .952 | 4.088 | .745 | **3.850** | **.876** | 4.294 | .628 | **4.1342** | **.50219** |
| **PNB Bank** | 4.175 | .718 | 4.356 | .781 | 4.061 | 1.091 | 4.071 | .868 | 3.588 | 1.414 | **4.153** | **.799** | 3.608 | 1.225 | 4.436 | .532 | 4.0919 | .57422 |
| **SBI Bank** | 4.130 | .629 | **4.542** | **.683** | **4.284** | **.731** | **4.277** | **.609** | **3.971** | **.994** | 4.033 | .624 | 3.688 | 1.013 | **4.608** | **.420** | **4.1876** | **.40430** |
| **F** | 32.660 | | 4.012 | | 46.108 | | 77.704 | | 3.121 | | 22.376 | | 7.853 | | 13.856 | | 53.822 | |
| **Sig.** | .000 | | .008 | | .000 | | .000 | | 026 | | .000 | | .000 | | .000 | | .000 | |
| **N** | 400 | | 400 | | 400 | | 400 | | 400 | | 400 | | 400 | | 400 | | 400 | |

Source : HRD Survey

Thus, the Null Hypothesis (H01) stands rejected and it is established that there were significant differences in between the banks understudy on their orientation towards HRD Mechanisms.

**Analysis of Relationship of HRD Mechanism with JS**

In view of analyze the impact between HRD Mechanisms with JS as an OP measure, Correlation was performed which suggested that HRD is positively correlated to JS r = .108 p = .000 n = 400.It was found that both share a positive association in between them and that the corelation is significant at 99 % level of significance (2-tailed). It is also inferred that among the components of HRD Index i.e. HRD Mechanisms, only the Training & Development (r = 0.168), Employee Involvement & Empowerment (r = 0.136), and Quality of Work life (r = 0.138) were having positive correlations with JS phenomenon which led the researcher to conclude that any incremental change in HRD Index or any of the above mentioned mechanisms will certainly bring about positive changes in the indemnification of bankers with many aspects of the job. Evidently, hypothesis H02(a) stands rejected and it stands established that there is a positive corelation between selected HRD mechanisms sharing a significant positive relationship with JS as an OP Measure. Table 8 is showing the significant results.

**Table 8: Correlation Matrix of Variables**

| | | **TD** | **PA** | **CPD** | **EIE** | **CRS** | **QWL** | **RAD** | **OC** | **JS** | **HRDI** | **Overall OP** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **HRD Mechanisms** | **TD** | 1 | | | | | | | | | | |
| | **PA** | .333** | 1 | | | | | | | | | |
| | **CPD** | .487** | .069 | 1 | | | | | | | | |
| | **EIE** | .461** | .290** | .660** | 1 | | | | | | | |
| | **CRS** | .100* | .546** | -.016 | .174** | 1 | | | | | | |
| | **QWL** | .401** | .299** | .526** | .594** | .308** | 1 | | | | | |
| | **RAD** | .416** | .145** | .620** | .442** | .081 | .561** | 1 | | | | |
| | **OC** | .110* | .168** | .100* | .121* | .307** | .285** | -.083 | 1 | | | |
| **Perceptual Measure of OP** | **JS** | **.168**** | .076 | .051 | **.136**** | .001 | **.138**** | .011 | .014 | 1 | | |
| | **HRDI** | .643** | .411** | .763** | .772** | .446** | .807** | .708** | .355** | **.108*** | 1 | |
| | **OverallOP** | **.123*** | .027 | **.202**** | **.215**** | .054 | **.104*** | **.101*** | **.151**** | .344** | **.207**** | 1 |

*p<.05, ** p<.01, *** p<.001
Source: HRD Survey

To achieve the H02(b) Multiple Regression with Stepwise Backward Method or Backward Elimination Regression was used for demonstrating the impact of eight mechanisms of HRD on JS measures as Organizational Performance.

Multiple regression analysis wasapplied to identify the contribution of eight HRD Mechanisms (mentioned above) towards influencing the JS (JOBSAT). The results show that R2 was .059 when all the eight predictors were included in Step 1. This shows that 5.9 percent of the variability in JS is associated with changes in the variables of TD, PA, RAD, CRS, CPD, EIE, and QWL& OC for this sample. The estimated coefficient of determination for the population (i.e., adjusted R2) is 3.9 percent. In Model 1, it was evident that the Potential Appraisal (PA) had a significant value of .823 which is greater than .05 at 5% level of significance; hence it was eliminated for the next step of regression analysis. In step 2 in the table, when the variable Potential Appraisal (PA) is removed, then there were no major variations in both these statistics, here R2 was .058 and estimated coefficient of determination (i.e., adjusted R2) is 4.2 percent. Similarly, in further steps, Organisational Culture (OC) (p value = .385), Compensation and Reward System (CRS) (p value = .168), Career Planning and Development (CPD) (p value = .272), Employee

Involvement and Empowerment (EIE) (p value = .383), were removed respectively for achieving the required Model fit. In all these steps the R2 slightly declines and estimated coefficient of determination (i.e., adjusted R2) stabilises. It has been seen in case of model 1, when all the eight HRD mechanisms (predictors) are entered, the significance level associated with the observed value of F (3.041) is .000 which is less than tabulated value. Thus, the Null Hypothesis H02(b) is rejected and it was concluded that there exists a significant linear relationship between the set of IVs (TD, PA, RAD, CRS, CPD, EIE, QWL & OC) and the DV (JOBSAT). Thus, the remaining three variables in Model 6 i.e., Training and Development (TD) (p value = .003), Quality of Work Life (QWL) (p value = .013) and RAD (Role Analysis and Development) (p value = .020) have significance value less than the default criterion and also has acceptable tolerance limits. Conclusively, it was inferred that JOBSAT (JS) shares a significant linear relationship with TD, QWL and RAD. Therefore, resulting regression equation is:

**Y (JS) = 4.554 + .205 (Training & Development) + .183 (Quality of Work Life) + .126 (Role Analysis & Development)**

This equation estimates that 4.7 percent of the variance in the DV (JS) is explained by the TD (Training and Development) QWL (Quality of Work Life) and RAD (Role Analysis & Development) in the selected organization's understudy. The underlying table 2 shows the results.

## Discussion

The research enriching the literature by highlighting the linkage between HRD Mechanism and Organizational Performance through perceptual measures of JS. The result of the research are extended prior research on HRD-OP with social science theory. Furthermore, study highlights that the HRD-OP have positive impact on JS of the employees in selected sector which is also proved by (Solkhe, & Chaudhary, 2011; Akdere, & Egan, 2020). Our results are showing a HRD practices have a significant impact on organizational performance and JS. It is suggested by Solkhe, & Chaudhary, 2011, as they found that HRD Climate reflects a direct effect on JS that causing to the increased organizational performance. The results reveal that employee perception towards HRD bankers' perceptions on account of HRD Mechanisms are observed to be significantly different in between the selected banks under this study and this difference is not by sampling or by chance, it is also proved by hypothesis testing as it is rejected with the 0.05 at 95% level of significance. While, Majumder, M. T. H., 2012 has suggested that in the private banking sector of Bangladesh HRM dimensions exercised is not satisfied to the employees, where employees are not satisfied with salaries, recognition and motivation, progress in carrer, training and development, management style, and job design and responsibilities. Here, our findings are differing from these finding and could be utilized strategically for further action.

The study also examined the relationship of HRD Mechanisms and JS which is taken as perceptual measure of OP. It reveal that there is strong corelation between HRD mechanisms and JS. Our data reveal that there is significance impact of HRD mechanisms on JS which leads to increase of organizational performance, these results are aligned with the results of (Katou, A. A., 2009; Solkhe, & Chaudhary, 2011; Akdere, & Egan, 2020). These findings have a greater scope of improving organizational performance and employee's satisfaction in the Indian banking sector more specifically to Delhi-NCR region.

## Table 9: Results of Multiple Regressions of JS

| | Model 1 | | | | Model 2 | | | | Model 3 | | | | Model 4 | | | | Model 5 | | | | Model 6 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | ***B*** | ***SE*** | ***B*** | ***p*** | ***B*** | ***SE*** | ***β*** | ***p*** | ***B*** | ***SE*** | ***β*** | ***p*** | ***B*** | ***SE*** | ***β*** | ***p*** | ***B*** | ***SE*** | ***β*** | ***p*** | ***B*** | ***SE*** | ***β*** | ***P*** |
| **(Constant)** | ***B*** | ***SE*** | ***B*** | ***p*** | 4.202 | .381 | | .000 | 4.399 | .306 | | .000 | 4.550 | .286 | | .000 | 4.559 | .286 | | .000 | 4.554 | .286 | | .000 |
| **TD** | 4.240 | .417 | | .000 | -.209 | .072 | -.170 | .004 | -.205 | .072 | -.167 | .004 | -.201 | .072 | -.164 | .005 | -.188 | .071 | -.153 | .008 | -.205 | .068 | -.167 | .003 |
| **PA** | -.204 | .075 | -.166 | .007 | | | | | | | | | | | | | | | | | | | | |
| **CPD** | -.019 | .083 | -.014 | .823 | .092 | .075 | .097 | .221 | .102 | .074 | .108 | .167 | .079 | .072 | .084 | .272 | | | | | | | | |
| **EIE** | .089 | .076 | .094 | .243 | -.098 | .074 | -.096 | .188 | -.105 | .074 | -.103 | .155 | -.094 | .073 | -.092 | .202 | -.057 | .065 | -.056 | .383 | | | | |
| **CRS** | -.095 | .075 | -.093 | .207 | .055 | .049 | .062 | .262 | .066 | .048 | .074 | .168 | | | | | | | | | | | | |
| **QWL** | .061 | .056 | .068 | .276 | -.211 | .089 | -.175 | .018 | -.188 | .085 | -.156 | .027 | -.154 | .081 | -.128 | .058 | -.153 | .081 | -.127 | .060 | -.183 | .073 | -.152 | .013 |
| **RAD** | -.211 | .089 | -.174 | .018 | .123 | .063 | .139 | .053 | .105 | .060 | .118 | .081 | .104 | .060 | .117 | .084 | .131 | .054 | .148 | .017 | .126 | .054 | .143 | .020 |
| **OC** | .123 | .063 | .139 | .053 | .067 | .077 | .049 | .385 | | | | | | | | | | | | | | | | |
| $R^2$ | .059 | | | | .058 | | | | .057 | | | | .052 | | | | .049 | | | | 0.47 | | | |
| ***Adj*** $R^2$ | .039 | | | | 0.042 | | | | 0.042 | | | | 0.040 | | | | 0.040 | | | | 0.040 | | | |
| *F* | 3.041** | | | | 3.476** | | | | 3.932** | | | | 4.327** | | | | 5.103** | | | | 6.553*** | | | |
| $\triangle R^2$ | .059 [a] | | | | .000 [a] | | | | -.002 [a] | | | | -.005 [a] | | | | -.003 [a] | | | | -.002 [a] | | | |
| $\triangle F$ | 3.041 | | | | .050 | | | | .755 | | | | 1.910 | | | | 1.212 | | | | .763 | | | |
| *N* | 400 | | | | 400 | | | | 400 | | | | 400 | | | | 400 | | | | 400 | | | |

*p<.05, ** p<.01, *** p<.001

## Conclusions

The study explored the linkages between HRD and organizational performance. Further, to see the impacts of HRD and OP on JS of the banking employees in the Delhi_NCR region. In nutshell, in the light of above aim of the study and based on the above analysis, application of statistical tests, and interpretation of the research results. The researcher concludes that HRD Mechanisms on a subjective measure of OP (JS), it is strongly evidenced that both share a positive relationship in such a manner that change in one will bring simultaneous changes in other. It is very well recognized though the magnitude of the relationship was not convincingly higher, in statistical terms it was enough to draw meaningful conclusions and justifiable to be explored in future research. It is also proved from the various regression results that HRD quite convincingly influences and impacts Organizational Performance to a considerable extent/levels supported by hypothesis H2b (as its get rejected). Additionally, findings also revealed that OP has constructive impact on the JS level of the employees and has circular relationship OP to JS to OP.

This study is being conducted on the banking employees; it has several policy implications. Primarily, as HRD mechanisms has a positive effect on JS, so these findings could be useful for the banking managers to improve the productivity and profitability of the employees. Secondly, JS itself a crucial component of employee's well-being, motivation, and their performance, therefore it could also be used as policy measure to motivate employees, enhance the well-being and performance of the employees in the organizations.

This is not holistic in nature as it carries some limitations. Firstly, it is being conducted on banking employees. It can further be extended to different sectors of employees to check the impacts of HRD practices on OP and JS. Secondly, the scope of this study was limited only to Delhi-NCR banking employees, again further studies can be done on different states, regions and countries, Additionally, comparative studies can also be conducted in future.

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# BOOK REVIEW

# AI Revolution In HRM: The New Scorecard

**(Authored by Ashwani Upadhyay, Komal Khandelwal, Jayanthi Iyengar, Published by SAGE Publications, 2020)**

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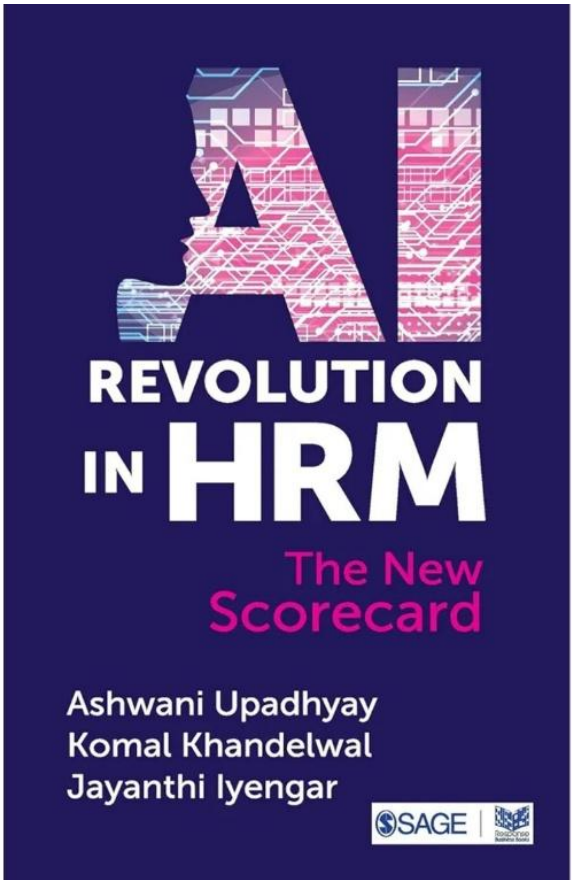


As we are living in the era of digital transformations, we know that an increase in technology will result in more digital transformations. This increase in technology is making AI more significant and relevant, leading it to act as a major force in determining organisational culture and competitiveness. It will also influence decision-making autonomy, along with organisational change management. Human resource management, earlier known for its human administration, coordination and relationships, now acts as data-infused and algorithm-driven. In AI Revolution in HRM: The New Scorecard, authors not only examine and analyse this shift from traditional to AI orientation but also propose a framework that is performance-oriented and reconceptualises HRM as a tech-enabled strategic move.

They not only position AI as an aid but also present it as a structural force that redefines workforce monitoring. According to them, AI adoption changes recruitment patterns, performance evaluation, learning structures and workforce analysis. Providing the concept of "new scorecard," this book poses a threat to traditional HR practices and advocates the idea of outcome-orientation performance evaluation metrics lead to organisational value creation.

The book follows a progressive analytical approach which highlights the importance of AI-oriented measures and, in the meantime, examines the limitations of conventional HR structure based on tackling complexity, scale of operations and especially the speed of task execution in case of modern age. The authors clearly stated how our old HR practices are inadequate to meet the vast demands of volatile and data-rich businesses.

The latter part examines the level of AI integration in HR core practices. They analyse predictive patterns in recruitment, talent identification, personalised learning platforms, models forecasting workforce distribution and workforce efficiency and monitoring real-time performances. This advocates real-time corrective approaches based on time-bound monitoring and leads to a transition from reactive approaches to preventive human resource measures, which will result in effective and efficient workforce management.
New scorecard framework development acts as an alternative to traditional dashboards of human resources. Organisational performance measurement, employee engagement, employee surveillance and productivity monitoring are some of the workforce indicators of AI-oriented measures that act as a central force leading to enhanced strategic outcomes. The book convinced organisations that most of its functions, like talent optimisation and inefficiency reduction, will be easily maintained and monitored through AI analytics. These practices reduce stress not only on resources but also on the workforce.

The book puts more stress on operational efficiency in comparison to change and the ongoing culture of organisations. It advocates the significance of digital transformations. According to the authors, digital transformations are not merely restricted to technological transformations. It also includes organisational training and learning, the capabilities of leaders and the degree of change acceptance by employees. It all somehow contributes to multidimensional approaches which include behaviour, cultures and develop a perfect balance between experience-based approach and evidence-based approach by integrating all in such a manner so that it will benefit the organisation in the long run. The book also helps in decision-making by utilising data-driven systems. The managers are getting more autonomy as they can exercise their authority and power without any issue. The book provides a clear, relevant and practical concept of technological optimism.

AI analytics is more focused about evidence based structures in comparison to experience-based parameters in human resources operations. Employee surveillance, examination, consent, and analysis, along with regulated institution results in a strong and deep critical path. The authors also consider ethical challenges with technological restrictions. Ethical challenges like transparency in procedures, privacy of employee data and technical bias occurred due to pre-set algorithms, and sometimes also include misrepresentation and manipulation of data plays a significant contribution to the modern challenges to AI-based systems. Automated systems sometimes create power imbalances as they only considers evidences.
Real-time illustrations and comparative case studies form a major part of the concepts help learners retain and apply knowledge whenever needed. It develops a robust methodology and approach that signifies empirical applications and inclination. Major implications of the book are as follows: It is a good source of knowledge for academicians, insightful for HR practitioners and organisational leaders, and provides guidance to policy makers about ethical oversight, bias-free algorithm design and regulatory compliance. The researcher and students of HRM can also refer to this for their academic as well as research purposes. It can help them build an empirical approach and motivate them to do more research in the related fields of AI adoption, efficiency and significance, especially in HRM practices taking place in organisations. It also helps them in data analysis of organisations, which will help them in figuring out exact deviations in results because of the use of tech-enabled, updated versions of models. All this led to effective and efficient data management and performance measurement, eventually employing the workforce in such a way that it will ultimately benefit the organisations. Algorithm-based decision-making not only needs trust but also paves the way for future research based on the data processed through AI models. AI models help in consistent workforce monitoring and surveillance of potential risks associated.

This book advocates approaches that lead to strategic analysis of AI processes in HRM as and when needed. It changes the patterns of performance evaluation and measurement. It reshapes workforce monitoring and surveillance and redesigns the critical engagement of employees. The book is a good contribution to modern HRM literature, highlighting all sorts of ethical and institutional challenges. It also advocates the significance of how AI transforms conventional HRM successfully by ensuring efficient analysis, accountability of practices and automation along with critical performance evaluation.

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