Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 7 | July-2026
ISSN (O) 3107-6696

Impact of Digital Automation on Operational Efficiency: The Mediating Role of IT Investment Intensity and the Moderating Role of Firm Size

Deepashree.P.Kulkarni
Dayananda Sagar college of Engineering- Dept of Management Studies
kulkarnideepashree4@gmail.com

---***---

Abstract - Digital automation - comprising artificial intelligence, robotic process automation, enterprise resource planning, cloud computing, and Internet of Things - is changing how businesses manage production, delivery of services, and decision-making processes. In this research paper, a theoretical framework and a testable model have been developed to investigate the effect of firm-level Digital Automation Index (DAI) based on content analysis of corporate disclosures on Operational Efficiency (OE) of Indian listed companies involved in automation-intensive industries such as industrial technology, manufacturing, engineering, automobiles, and electronics. Based on the Resource-Based View and Dynamic Capabilities perspective, the testable model asserts that IT Investment Intensity (ITI) acts as a mediator between DAI and OE, and Firm Size (FS) moderates their relationship. A panel data approach for the years 2020-2025 involving 30-50 listed firms (180-300 observations) has been suggested, using secondary data sources such as annual reports, sustainability reports, and financial statements. This paper describes how Digital Automation Index will be calculated, operationalize all the constructs, provides five hypotheses, and presents a nine-phase statistical analysis method including descriptive statistics, panel diagnostics, fixed or random-effects regressions, mediation and moderation analysis, and robustness tests.*Key Words:* digital automation, operational efficiency, IT investment intensity, firm size, Industry 4.0, panel data, Indian listed companies.

1.INTRODUCTION

1.1 Background

Digital technologies such as AI, RPA, ERP, Internet of Things (IoT), and cloud computing have shifted from being auxiliary IT initiatives to key elements in shaping the way businesses compete. Digital transformation can be seen better in its essence as not the acquisition of one specific technology but a continuous socio-structural shift through which digital technologies help create value and competitive advantage. In the context of this broader paradigm shift, digital automation – performing operational activities using software and machines with little human intervention – has been recognized as a direct driver of operational success: innovative technologies like automation, AI and IoT have proven to bring significant increases in operational efficiency, which lead to cost reductions and profitability

Empirical support for this position has been growing quickly within diverse settings. Digital technologies, including AI, IoT, and big data analytics, have been found to increase total factor productivity in manufacturing organizations through better allocation of resources and preemptive discovery of production bottlenecks which would otherwise result in losses. In services and back-office environments, systematic review of robotic process automation reveals an estimated reduction in operational expenses of around 30% to 70% in automated financial processes, along with increases in productivity of up to 85% in repetitive tasks, such as account payable and account receivable processes. The more recent survey evidence based on implementation of RPA and AI indicates that these technologies represent complementary automating and augmenting resources which, in accordance with the resource-based view of the firm, yield cost savings and revenue effects. Overall, these studies imply that automation should not be viewed merely as an information technology issue, but rather as a firm capability having implications for cost structure, cycle time, and asset management, all of which form the essence of operational efficiency.

1.2 The Indian Context

This is the process being experienced by India's manufacturing and industrial technology industry. The investment in Industry 4.0 by India's manufacturing industry has increased by roughly ten times in the last ten years, with digital technology expected to form an even larger share of the total cost of manufacturing technologies in the middle of the next decade than a few years. India's large businesses have significantly higher levels of digital maturity than medium and small-scale enterprises, indicating a positive correlation between firm size and level of automation as well as its benefits (CII, 2025). On the other hand, digital transformation is considered critical in increasing competitiveness as well as optimizing operations in India's manufacturing industry, which accounts for a sizable percentage of the nation's gross domestic product and exports (EY India, 2025). Government initiatives – Digital India, Make in India and sectoral programs like SAMARTH Udyog Bharat 4.0 – are specifically designed to make sure that the transition involves more than just the most well-resourced companies. It should also be noted that sectoral data indicates that India's manufacturing industries in the automotive and electrical/electronic categories are disproportionately represented in Industry 4.0.

It is precisely such a skewed diffusion process that makes India an important venue for the current study. In case the effect of automation on productivity was independent of any firm-level variables, all one had to do was to speed up the pace of adoption. However, in case the effectiveness of automation is contingent upon the extent of investments in IT and firm size, policies would have to be considerably more focused by targeting the particular capabilities lacking in medium-size firms that do not enjoy the same degree of efficiency improvements from automation spending as larger companies.

1.3 Problem Statement and Research Gap

Nonetheless, at least three deficiencies exist in the empirical literature. First, perceptual measurements of digitalization used in studies on operational efficiency tend to be based on survey responses that use Likert-scales and thus capture managers' perceptions of the level of digitalization of the organization. Such a measure is hard to generalize across studies, suffers from common method variance, is affected by social desirability bias, and tends to be unavailable in sufficient samples to conduct longitudinal analyses of listed firms. Second, even though there is an ample literature analyzing the relationship between adopting digital technology and performance, very little is known about how automation results in greater efficiency and what moderating factors affect this process in an emerging country like India where the use of objective measures in secondary data is possible. Third, most of the available studies on Industry 4.0 adoption in India have descriptive nature — market sizing reports and adoption surveys conducted by industry associations.

These gaps are important since there remains an empirically significant issue for the Indian management and policy makers: is the efficiency evidence on digital-automation generalizable for firms of all sizes and with varying degrees of complementary IT investments, or does the observed efficiency gain occur for the biggest and most resourceful firms? In the absence of a replicable, secondary data-based method to address this issue, the firm-level investments and policies could be made using cross-national evidence which might be unrelated to the nature of digitalization in India.

1.4 Research Objectives

The present research paper attempts to fill these gaps by suggesting (i) an index for Digital Automation (DA) based on annual and sustainability report information (DAI) without using any subjective survey-based measures and (ii) a mediated moderated framework where Information Technology Investment Intensity (ITI) is suggested to serve as one of the pathways through which digital automation has impact on operational efficiency (OE) and firm size (FS) is suggested to moderate this relationship, which can explain the presence of greater absorptive capacities and resources of bigger firms to use their investments in digital technologies more effectively (Ghofar et al., 2025; Luo & Yu, 2022). More precisely, the current research seeks to: (i) develop and operationalize Digital Automation Index based on secondary disclosures; (ii) investigate the direct impact of digital automation on operational efficiency in Indian listed firms in industries characterized by automation; (iii) explore the role of IT Investment Intensity as a mediator of the impact of automation on efficiency; (iv) investigate the moderating role of firm size in this relationship; and (v) develop a plan for full-fledged panel data statistical analysis, which will be implemented once disclosure data will be gathered.

1.5 Significance and Scope of the Study

The sample scope is limited to Indian listed firms in industrial technology, manufacturing, engineering, automobile and electronics – sectors highlighted in industry reports as being most advanced in implementing Indian Industry 4.0 solutions – over the 2020-2025 period. The choice of scope is deliberate in that it is more narrowly focused than that of an economy-wide study: industries that rely heavily on automation are selected in the hope that disclosures about such automation initiatives are not generic but substantive. There are three reasons why the study is important.

First, it contributes to the academic literature on digital transformation and IT value by applying the concepts to the Indian case. Much of this literature uses Chinese, European or North American data. Second, methodologically, it provides a clear and reproducible procedure for constructing a digitalization index from publicly available disclosures, reducing dependency on survey datasets. Third, practically, it provides a framework that is empirically testable for managers, investors and policymakers interested in identifying when, and for whom, investments in digital automation can pay off.

1.6 Structure of the Paper

The rest of the paper is structured as follows. In Section 2, I review the relevant theoretical and empirical literature on digital automation, the relationship between investment intensity in IT and firm size, and build up the theoretical basis of the proposed model. Section 3 introduces the research framework and five hypotheses. Section 4 outlines the proposed methodology, which includes sampling and data sources, creation of Digital Automation Index, operationalization of variables, and a nine-phase statistical methodology. The theoretical and practical implications of the research are discussed in Section 5. Section 6 highlights the weaknesses of the proposed model and further research directions, while Section 7 concludes.

2. LITERATURE REVIEW

2.1 Theoretical Foundations

Two conflicting theories have been put forward as the basis for this research work. First, according to resource-based theory (RBV), sustainable competitive advantage arises as a consequence of a business's management of valuable, rare, inimitable and non-substitutable (VRIN) resources. Automated technologies, such as software, artificial intelligence models, ERP systems, as well as information produced by these resources, are more and more considered to be a unique kind of resource because of the ability of digital automation to upgrade already existing tangible and intangible resources of the firm and make it difficult for competitors to duplicate it fast enough, especially within the firm's unique processes (Arshad et al., 2025). Through the lens of RBV theory, digital automation will provide efficiency as a result of its application as the real capability of the business.

The suggested approach goes one step further, stating that in addition to having valuable resources, the firm should be capable of identifying opportunities and exploiting them through timely investments as well as reorganizing itself to take advantage of the technological changes. Diffusion-of-innovation theory may prove to be a decent supplement to the two suggested theories, explaining why the influence of automation on efficiency will differ systematically depending on the size of the firm – larger organizations typically possess more absorptive capacity, extra resources that guard against the risks related to the implementation of innovation, and greater negotiating power towards the technology vendors.

As for the dynamic capabilities approach, it is capable of providing justification of the IT Investment Intensity as a mediator in this study, since IT automation projects mentioned in annual reports demonstrate the firm's strategic vision, and IT expenses are necessary to bring it to life.

2.2 Digital Automation and Operational Efficiency

An increasing number of papers show a relationship between digital technology uptake and efficiency increases. Digital transformation was found to lead to an increase in operational efficiency among manufacturing companies due to the reorganization of the company's valuable, rare and difficult-to-reproduce technological resources according to the resource-based theory of competitive advantage that states that competitive advantage depends on the uniqueness of the set of tangible and intangible resources possessed by the company, such as technologies and processes. The use of the text-analysis approach to the measurement of digital transformation through data obtained from annual reports of companies has been applied in previous studies in order to ensure greater objectivity of measurement; this is the approach adopted for Digital Automation Index in this research paper.

Additional evidence coming from Central and Eastern European context shows that there is a statistically significant difference in terms of total assets, income, and shareholders' money among companies with a higher degree of digitalization compared to other firms (Valaskova et al., 2025).

There is also clear evidence on the level of individual automation technologies that support this trend. Systematic reviews of robotic process automation show considerable savings in operational costs – typically ranging from 30 to 70 percent – in financial and administrative processes that have been automated, as well as increased productivity by up to 85 percent for repetitive tasks with high volume and rules-based activities, as well as shorter financial cycles, better working capital management, and reduced errors in account payables and account receivables operations. There are sector-specific cases which confirm the above trends: the use of robotic process automation along with machine learning technology in predictive maintenance has produced notable improvements in the average time between failures as well as significant savings in the average time to repair and unplanned downtimes, thus demonstrating that the efficiency effect of automation technology works through actual operations rather than just financial indicators. Indeed, in light of the recent survey data regarding the combination of RPA and AI, the benefits of automation vary depending on the performance indicator, with the combination of RPA and AI being positively associated with costs savings as well as each individual technology's effect on costs but the extra benefits arising specifically from the combination of both technologies being related to revenue increases and not further costs savings. Such considerations suggest using ratio-based performance indicators based on asset utilization (asset turnover and operating margin) to measure Operational Efficiency, which are directly tied to automation effects on costs and throughput.

2.3 IT Investment Intensity as a Mediating Mechanism

Classic research on information systems showed that there is no straightforward connection between IT investment and company performance because this connection can be viewed as indirect and realized via intermediate value creation stages. This crucial theoretical foundation which shows that there is no immediate effect of IT spending on performance but it should be transformed into capability is used in the present model to treat IT Investment Intensity as a mediator, rather than a control variable. Continuing this tradition, the latest research supports the idea that IT investment management is a mediator for its translation into firm performance: in particular, in a study carried out on Chinese companies, structured governance of IT value was shown to be a mediator between IT investment dimensions and firm performance. Another stream of research on business-IT alignment shows that there is also no direct link between management of IT investments and firm performance but it goes via alignment as an intermediate stage using survey data gathered from IT and business managers.

This makes it reasonable to treat IT Investment Intensity as a mediating rather than moderating factor: Digital Automation is normally associated with IT capital expenditure, and it is precisely the employment of IT resources in the organization's operation, and not only the disclosure of such efforts, that leads to positive results in operations. In the same way, the research on R&D and technology investment intensity has demonstrated that the level of technology investment intensity impacts the effect of certain digital efforts or integration processes in terms of their effect on organizational performance within manufacturing organizations, where investment intensity was able to reduce the negative spillover effects of some integration processes and to strengthen others (Zhou et al., 2025). Even though in this research the intensity of technology investment is considered as a moderator of supply chain integration, the core idea of this research is that the level of investment in technologies affects the relation between upstream digital effort and downstream performance, which indirectly confirms the appropriateness of modeling it as a mediator of digital automation in our framework.

2.4 The Moderating Role of Firm Size

The size of the firm is another boundary condition that is regularly mentioned in digital transformation research. According to evidence gathered among ASEAN manufacturing firms, firm size substantially moderates the impact of digital transformation on financial measures such as capital structure due to the fact that larger firms are able to cover the high fixed costs of digital investments through diversification over a greater operating base. As for Chinese pharmaceutical companies, there is evidence that firm size has a positive moderating impact on the link between readiness to transform in an internal and external manner and the actual extent of digital transformation using structural equation modeling of several hundreds of firms (Luo & Yu, 2022). There is further complementary evidence in the area of capital allocation according to which larger firms derive more benefits out of digital transformation in terms of operations in the short term, taking advantage of resources required for implementing complex digital treasury and cash management solutions, while smaller firms derive such benefits in the long term as the cost of entry decreases due to the cloud technology.

With more resources at their disposal, larger companies are in a good position to finance the implementation of ERP and automation across their whole company, hold onto skilled digital talent and get favorable terms from the technology vendors, thereby enhancing the impact of digital automation on efficiency. In addition, size heterogeneity within the SME sector and the role played by factors like management education and internationalization in influencing the positive impact of size on digitalization have been documented in studies on digital transformation in SMEs. The above findings, taken together, serve as justification for the inclusion of Firm Size as a moderator, not just a control variable, in the current study design.

2.5 Automation, Cost Structure and Process-Level Efficiency

There is also a relevant body of parallel literature investigating the efficiency impact of automation at the level of particular business processes and not across aggregated firm-level financial metrics, which serves to provide useful guidance on the choice of content analysis keywords underlying construction of the Digital Automation Index within the current study. Indeed, research into automation of workflow and robotic process automation of finance operations finds that the automation of the process of accounts payable and receivable helps to reduce the financial cycle length and enhance working capital management practices, and systematic reviews across healthcare, education and manufacturing show a number of consistent results of reductions in time, errors and costs resulting from introduction of RPA, although the magnitude of the effects differs greatly across different sectors and different types of processes. For instance, RPA-based automation of attendance and reporting processes within administration of higher education institutions has been found to lead to very large reductions in processing times and moderate reductions in multiyear costs of operation, which indicates that the efficiency channel works through tangible reductions in the manual processing time and not through the general performance of the firm.

2.6 The Indian Context and Research Gap

This research question is set against a unique backdrop in the case of India. Investments in Industry 4.0 technologies by Indian businesses have increased ten-fold in the last decade, and the trend shows no signs of slowing down (CII, 2025). However, the level of digitalisation remains skewed, as large companies show significantly higher automation-maturity scores compared to medium and small firms, and the difference between the highest and lowest quartiles of companies is significant. Implementation cost, difficulty of integration with existing systems and labour concerns are more pronounced among smaller Indian companies while the leaders of automotive, electronics, and pharmaceutical industries are implementing their smart factory projects. Government projects like Digital India and Make in India are designed specifically to address this problem and increase the number of companies that use automation (EY India, 2025). Thus, India constitutes a good environment to test the hypothesis that IT investments and company size together contribute to efficient use of automation by some companies while others fail in this respect.

Table-3: Summary of Key Reviewed Studies

Study	Context / Sample	Key Finding Relevant to This Study
Valaskova et al. (2025)	Cross-country, Orbis database	Digitalization associated with significant differences in financial performance; automation and IoT linked to efficiency gains.
Harris & Katz (1991)	U.S. insurance industry	Foundational construct of IT investment intensity; performance effects operate indirectly.
Hitt & Brynjolfsson (1996)	U.S. firms, multiple industries	IT value materializes through productivity and consumer-surplus channels, not direct profit alone.
Ilmudeen & Bao (2019)	176 Chinese firms	Managing IT investment mediates the IT–firm

Journal Publication of International Research for Engineering and Management (JOIREM)
Volume: 04 Issue: 7 | July-2026
ISSN (O) 3107-6696

		performance relationship.
Zhou et al. (2025)	1,038 Chinese manufacturing firms	R&D/technology investment intensity conditions how integration efforts translate into performance.
Ghofar et al. (2025)	2,490 ASEAN manufacturing firms	Firm size significantly moderates the digital transformation–financial outcome relationship.
Luo & Yu (2022)	395 Chinese pharmaceutical firms	Firm size positively moderates digital-transformation readiness and depth.
Arshad et al. (2025)	Two international firm surveys	RPA and AI are complementary automating resources with distinct cost- and revenue-side effects.
CII (2025)	Indian manufacturing sector report	Large Indian enterprises show materially higher digital-maturity scores than mid/small firms.

Synthesizing from this review, there are three reasons which underpin the need for the current study. To begin with, there is clear international empirical evidence of a positive direct association between digital automation and efficiency, which, however, is based predominantly on Chinese, European, and international survey data rather than Indian firm-level disclosure-based data. Next, IT investment intensity is well established in theory and empirical evidence to be a mediator rather than just a control, but the former has been very seldom analyzed along with a disclosure-based automation variable in an Indian panel data context. Finally, firm size is well established as a consistent moderator of digital transformation outcomes, but has not been analyzed so far with regard to the relationship between automation and operational efficiency for Indian listed firms.

3. RESEARCH FRAMEWORK AND HYPOTHESES

By combining the resource-based view theory and dynamic capabilities theory, the study introduces the mediational moderated model where Digital Automation (DAI) influences Operational Efficiency (OE) directly as well as indirectly via IT Investment Intensity (ITI), while the impact of such relationship moderated by Firm Size (FS). The proposed research framework is presented in Fig. 1.

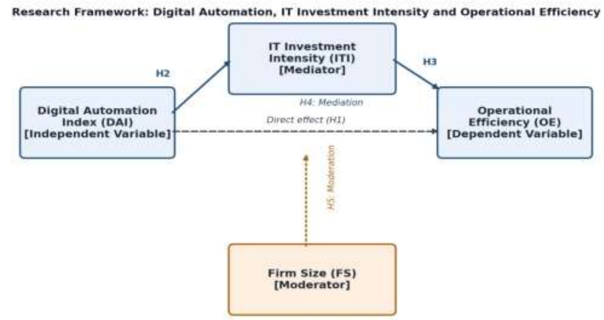

Fig-1: Research Framework

3.1 Hypothesis Development

H1: Digital Automation has a positive impact on Operational Efficiency. Companies that provide information on their higher levels of automation compared to just mentioning their digital efforts are anticipated to have higher asset turnover ratio and operating margins, as has been found to be true in cross country research where technologies involving automation were found to improve operational efficiency and reduce costs (Kamble et al., 2020, as cited in Valaskova et al., 2025), and in process level research showing cost and time reduction after the adoption of RPA.

H2: Digital Automation has a positive effect on IT Investment Intensity. Any automation efforts disclosed such as ERP implementations, RPA implementations, or IoT-based monitoring normally need continuous investment to put into place and sustain the processes. It is expected that the DAI scores are positively correlated to IT investments in relation to sales or asset sizes due to the logic of dynamic capabilities.

H3: IT Investment Intensity is positively related to Operational Efficiency. Following the seminal research showing how the impact of IT on performance occurs through a set of intermediate steps of creating value (Harris & Katz, 1991; Hitt & Brynjolfsson, 1996) and new studies supporting the mediation role of managed IT investments in organizational performance outcomes , it is anticipated that high IT investment intensity will be positively related to operational efficiency, regardless of automation disclosures prompting such investment

H4: The mediating role of IT Investment Intensity in the Digital Automation - Operational Efficiency Relationship. The combination of hypotheses 2 and 3 leads to a proposition that there exists significant transmission of the impact of digital automation on operational efficiency via the intensity of IT investment induced by it, and not through the purely direct influence. The hypothesis explicitly tests the claim made by the resource-based theory about the need for transformation of resources (disclosure of automation) into capabilities (investment in IT).

H5: Firm Size has a positive moderating effect on the relationship between Digital Automation and Operational Efficiency. In line with the results suggesting that firm size enhances the conversion of digital transformation into financial performance among ASEAN manufacturing companies (Ghofar et al., 2025) and has a positive moderating effect on digital transformation readiness among Chinese pharmaceutical companies (Luo & Yu, 2022), it is anticipated that larger listed firms from India will translate a given amount of digital automation into higher levels of operational efficiency than their smaller counterparts.

4. RESEARCH METHODOLOGY

4.1 Research Philosophy and Design

The research will take on a positivism research philosophy with deductive reasoning approach, aligned to the hypothesis testing purpose indicated in section 1.4, wherein theory (resource based view, dynamic capabilities) is employed to deduce hypotheses that can be tested by empirical measures through secondary data (as opposed to survey perceptions). The proposed research design for this study will be an ex-post-facto panel data design using secondary data from Indian listed firms in automation dependent industries – industrial technology, manufacturing, engineering, automobile and electronics from the years 2020-2025 (6 years). The use of panel data as against cross sectional single year design is justified for three reasons: 1) it helps in absorbing time invariant firm specific effects in the form of firm fixed effects (unobservables like management quality, legacy technology stock); 2) it provides enough statistical power to detect moderation-mediation effect (which requires larger sample size as compared to a direct effect test); and 3) it helps in examining whether the automation efficiency linkage intensifies through the sample period as Indian Industry 4.0 gets entrenched.

4.2 Population and Sample

The target population comprises Indian listed companies falling in the category of automation-intensive industries as per the definition in Chapter 1.5. Purposive (judgmental) sampling is preferable to simple random sampling because the Digital Automation Index demands sufficiently detailed public disclosures in the form of annual reports, sustainability reports, and investor presentations, in order to enable content-analysis scoring, and most small-listed companies make limited disclosure that would add too much missing data noise in the DAI. The recommended purposive sample size of 30 to 50 companies will result in 180 to 300 firm-year observations over 6 years – a sample size that is more or less similar to that in comparable secondary data-based digital transformation studies using fixed/random-effects panel regression. Firms having less than four years of consecutive disclosure during the sample period should be dropped to maintain a balanced panel. The sample needs to be verified in terms of coverage of large-cap, mid-cap, and selected automation-intensive small-cap companies to allow estimation of the moderator variable – Firm Size.

4.3 Data Sources

Potential sources for candidate information can be annual reports of firms, sustainability/ESG reports, presentations by investors, filings from stock exchanges, and commercial databases like CMIE Prowess or Capitaline wherever possible to validate financial factors such as total assets, revenue, operating profit and total debt. In the case of firm IT or digital capital expenditures not being provided separately, the candidate needs to refer to the footnotes and MD&A to find any breakdown of technology spending before considering any proxies discussed in section 4.6. It is preferable to double check all financial variables using at least two sources (such as annual reports and commercial databases).

4.4 Construction of the Digital Automation Index

Given that there is currently no standardized Digital Automation Index, this study suggests creating one based on content analysis of text contained within annual reports and sustainability reports, similar to how text analysis was used for measuring digital transformation in previous studies to increase objectivity compared to surveys. The keyword list – "artificial intelligence," "machine learning," "robotic process automation," ERP, "SAP/Oracle implementation," cloud computing, IoT, Industry 4.0, "digital twin," "predictive analytics," "smart factory," "automation," "digital platform," and "data analytics" – will be coded per company-year using the four-point scale in Table 2 and the resulting scores added or averaged together to create the DAI. This scaled scoring method is meant to differentiate between companies simply mentioning a technology and those who discuss implementation of the technology with concrete outcomes, which is substantiated by empirical evidence that efficiency gains from automation depend on thorough and process-oriented implementation.

For the purpose of establishing the reliability of the research, the researchers suggest that at least two different independent coders code a selected sample (around 20 percent of the sample size) of disclosures in firms over various years, and the inter-coder reliability will be analyzed based on Cohen's kappa test; in case the value of kappa is less than 0.70, then there must be modification in coding guide and coder training before proceeding with coding of the entire sample. When natural language processing software is used for detecting the keywords, then validation of the randomly selected sample is suggested.Table-1: Variable Definitions and Data Sources

Variable	Type	Measurement	Data Source
Digital Automation Index (DAI)	Independent	Content-analysis score of annual report / sustainability report disclosures on AI, ERP, RPA, cloud, IoT,	Annual reports, sustainability reports

		digital twin, automation and analytics (0–3 scale per keyword, summed/averaged)	
Operational Efficiency (OE)	Dependent	Asset Turnover Ratio (Sales ÷ Total Assets) or Operating Margin (Operating Profit ÷ Revenue × 100)	Annual reports, financial statements
IT Investment Intensity (ITI)	Mediator	IT expenditure ÷ Revenue, or IT/digital capital expenditure ÷ Total Assets	Notes to accounts, annual reports
Firm Size (FS)	Moderator	Natural log of total assets, ln(Total Assets)	Annual reports
Firm Age	Control	Years since incorporation	Annual reports
Financial Leverage	Control	Total Debt ÷ Total Assets	Annual reports
Sales Growth	Control	Annual percentage change in revenue	Annual reports
Industry Type	Control	Industry dummy variables	Company classification

Table-2: Digital Automation Index — Scoring Rubric

Score	Meaning
0	No disclosure of the technology/practice
1	Mention only, no implementation detail
2	Implementation discussed
3	Extensive implementation with measurable/reported outcomes

4.5 Operationalization of Constructs

The dependent variable, Operational Efficiency (OE), is primarily measured using the Asset Turnover Ratio (Net Sales/ Average Total Assets) that measures the degree of the company's efficiency in transforming the asset base into revenues. The Operating Margin (Operating Profit/ Revenue *100) will be considered as the alternative dependent variable for conducting the robustness test. This is because while the operating margin measures cost/revenue relationship in a business, the asset turnover ratio measures the ability of a firm to transform its assets into revenues. The mediators, IT Investment Intensity (ITI) are defined as IT expenditure/revenue ratio. Alternatively, when expenditure/revenue data is not available, the ratio can also be calculated as IT/ digital capital expenditure/total assets. This definition follows the classical definition of the IT investment intensity variable commonly used in information systems literature (Harris & Katz, 1991). The moderator, firm size (FS), is defined as the natural log of total assets (ln(total assets)). This definition of firm size is similar to the one used in previous moderation studies (Ghofar et al., 2025).

Control variables used to minimize the risk of omitted variable bias are:

- Firm Age (number of years elapsed since the firm was incorporated), acting as a proxy for organizational learning and legacy system problems;
- Financial Leverage (Total debt/Total assets), which is used to control for the influence of capital structure on business operations;
- Sales Growth (rate of increase in sales per year) controlling for independent demand side factors that may influence asset turnover;
- Industry Type, using industry dummy variables.

4.6 Statistical Analysis Plan

The suggested analysis consists of nine stages. Stage 1 will deal with data preparation and will include handling missing values, detecting outliers based on boxplot or interquartile range approach, and transforming variables in a way like ln(Total Assets), and applying the winsorization of financial ratios at 1st and 99th percentiles in order to reduce the impact of extreme values that often appear in ratio-based financial data. Stage 2 involves calculating descriptive statistics (mean, median, standard deviation, minimum, maximum, skewness, kurtosis) for all variables, both for pooled and yearly samples in order to detect structural breaks around the time of COVID-19 recovery period within the sample from 2020 to 2025. Stage 3 estimates Pearson correlation coefficients along with creating a corresponding heatmap in order to have an overview of bivariate relationships between DAI, ITI, OE, FS and control variables. Stage 4 includes running multicollinearity diagnostics using VIF and tolerance statistics with the criterion of 10 (or 5) for VIF used in order to detect collinearity issues (which is especially important considering possible high correlation between DAI and ITI).

Phase 5 tests the panel data for diagnostics before estimating the model: Pesaran cross-sectional dependence (CD) test to test if the firm level errors are cross-sectionally correlated (given the common shocks to firms), the Levin-Lin-Chu test or Im-Pesaran-Shin unit-root tests to check if the panel series is stationary, Breusch-Pagan or Modified Wald test for testing group wise heteroskedasticity and Wooldridge test for serial correlation in the panel errors. Phase 6 estimates the panel regression model using the two models - fixed effects and random effects and chooses between the two by the Hausman test. Given the possible correlation between firm specific unobservable heterogeneity such as quality of management and the regressors, fixed effects specification will be preferred, but both should be reported for transparency.

In Phase 7, a mediation analysis is done using the Baron and Kenny stepwise method as the first diagnostic test, and then bootstrapped indirect effect estimation (preferred over the Sobel test because of its more robust treatment of non-normal indirect effect distributions) is done to estimate the direct effect of DAI on OE, indirect effect mediated by ITI, and total effect in the panel data context. Phase 8 involves moderation analysis where a mean-centered interaction variable, DAI x Firm Size, is created and entered in the regression along with its constituent variables and plotting simple slopes at low (mean – 1SD), mean, and high (mean + 1SD) values of Firm Size where the interaction effect is statistically significant. Phase 9 involves conducting robustness tests by clustering of standard errors by firm, estimating the regression using Operating Margin in place of Asset Turnover, and conducting sensitivity analysis which runs the core model without largest and smallest firms in the sample.

Baseline Regression Model Specification

The baseline regression model is expressed as follows:

$OEit = \beta0 + \beta1DAIit + \beta2ITIit + \beta3FSit + \beta4(DAIit \times FSit) + \Sigma\ \beta k\ Controlsit + \mu i + \varepsilon it$

where subscripts i and t represent firms and years respectively; μi refers to firm fixed effects, while εit represents idiosyncratic errors. A second regression equation, which complements this model is $ITIit = \gamma0 + \gamma1DAIit + \Sigma\ \gamma k\ Controlsit + \mu i + \varepsilon it$, which will be used for mediation analysis in phase 7.

4.7 Validity, Reliability and Ethical Considerations

Validity of Content for the Digital Automation Index is ensured by using the keyword set based on the language employed in various peer-reviewed academic articles related to digital transformation and industrial reports in India, rather than just coming up with an arbitrary set of keywords. Validity of Construct for Operational Efficiency and IT Investment Intensity is ensured by their adherence to the widely-used definition of financial ratios that were used in previous information systems and corporate finance literature (Harris & Katz, 1991; Hitt & Brynjolfsson, 1996). Since all data comes from publicly available sources and commercial databases, no informed consent process is required for this research, unlike in surveys; however, all data must be managed according to the policies of the research institution where it is conducted.

4.8 Indicative Timeline and Resource Requirements

Implementing the proposed research method is a complex process that should be explicitly designed rather than considered to be one-step of data collection. The illustrative timetable shows that about four to six weeks will be needed to finalize the sampling frame and test disclosure feasibility by the help of a pilot content analysis mentioned above in Chapter 4.9; about eight to ten weeks will be required to finish content-analysis scoring of the Digital Automation Index for the whole sample of company-years, including the interrater reliability analysis; four to six weeks will be necessary for collecting manually and cross-validating the financial and IT expenditure variables from annual reports and, if possible, commercial databases; and another four to six weeks for cleaning and diagnosing the data, estimating models, and conducting robustness tests. In other words, the estimated implementation time will be about five to six months for one person researcher or less with the coding group esource requirements are few but important: access to the annual reports of the companies (which is generally available free from the website of the companies' investor relations department or from the National Stock Exchange/Bombay Stock Exchange system), access to CMIE Prowess or Capitaline for verification purposes, and software that can perform analysis using panel data (Stata, R, or Python).

4.9 Feasibility Note

However, disclosure of information technology expenses is not guaranteed across all firms listed in India. If there arises a situation where a company has not disclosed its digital or IT expenses individually, it would be recommended to use a constant proxy measure such as digital transformation investment expenditure, technology-related capital expenditures, or even the capital intensity or R&D intensity in extreme situations as an alternate mediator. Piloting must be undertaken through the process of content analysis of about five to ten companies before the full-scale data collection in order to validate the rubric as well as ensure the adequacy of firms disclosing IT expenses to include them in the sample.

5. EXPECTED CONTRIBUTIONS AND IMPLICATIONS

This work will be discussed as a research framework and methodology paper, not an empirical one since the Digital Automation Index needs to be calculated manually or semi-manually by performing the content analysis of firm disclosure statements while the data on IT expenditure should be collected manually from notes to accounts, which cannot be replaced by a literature review. Upon implementation, the proposed model is supposed to contribute to the literature on the following levels.

5.1 Theoretical Contributions

First, switching out survey-based digitalization constructs for a more objectively measurable, disclosure-based DAI construct should lead to increased replicability of digital-transformation research in the context of India, where access to large samples of listed firms is not possible, and the rate of responses to surveys of executives in academia is generally low. Second, the formal testing of IT Investment Intensity as a mediator, instead of relying on an automation–efficiency relationship, will address evidence from a long time ago that the influence of IT on performance occurs indirectly via value creation at the intermediate stage. In doing so, it will apply the classical theory of value creation by IT to its automation aspect specifically, something which has not been done as much before with this formal approach. Third, Firm Size as a moderator instead of a control variable directly tests whether the known size gradient in digital maturity in India leads to a similar size gradient in the efficiency gains of automation.

5.2 Methodological Contributions

The paper provides a clear, four-level content analysis scorecard for digital automation disclosure (Table 2) that is amenable to consistent application across firms and years along with a clear method of measuring inter-rater reliability. It aims at addressing a recognized drawback within the digital transformation literature, which is that many of the indices used in this field are either proprietary, non-transparent with respect to construction, or based on single-coder judgment without any measure of inter-rater reliability. With a pre-specified list of keywords, scoring system, and coder training methodology, the approach taken here is amenable to replication by other researchers examining other industries, different years, or even other countries, allowing DAI scores to be compared across studies.

5.3 Practical and Policy Implications

From an implementation point of view, a proven mediation effect (H4) will mean that there will be a need to account for automation investments as IT investment projects with intensity measures as opposed to technology purchases where the benefits can just be assumed but not measured. The chief financial officers and operation management of the organization will be able to apply the three metrics of OE, ITI, and DAI proposed in this study as a simple internal dashboard to gauge whether automation investment projects are supported by the required IT investment measures.

Moderation effect H5 would imply that medium-sized and smaller Indian manufacturers require additional capabilities support of the type that Digital India, Make in India, and SAMARTH Udyog Bharat 4.0 initiatives (EY India, 2025; CII, 2025) are providing in order to make automation deliver the same productivity benefits as achieved by larger firms. For policy-makers, it will allow using company level empirical evidence in addition to a general observation made in Indian industry reports about a high degree of digital maturity on the side of large companies and the necessity for special automation support programs for MSMEs. For investors and equity analysts, a validated DAI can be used as an additional screening variable based on disclosures to identify automation intensive companies with higher probabilities of translating their digital strategies into operations results, in addition to ESG and corporate governance screens.

5.4 Positioning Relative to Prior Evidence

The anticipated results can be tentatively compared to the existing literature even before the primary data collection begins. The acceptance of hypothesis H1 will mean that the Indian result is consistent with the larger international experience regarding how digital technologies boost operational efficiency and total factor productivity (Valaskova et al., 2025), although this consistency would now be based on a disclosure measure instead of survey data. The acceptance of H4 will mean that the indirect-value process through managed IT investments identified by Ilmudeen & Bao (2019) for China holds for India as well, confirming the relevance of this indirect mechanism beyond a particular national context and supporting the early literature on IT and productivity .

If H5 were supported, then the Indian moderation result would join existing size-based moderation effects in ASEAN manufacturing and in the Chinese pharmaceutical sector (Luo & Yu, 2022). The robustness of firm size as a moderator of digital transformation outcomes could thereby be further demonstrated across multiple countries. However, if no significant relationship were found in support of any of the hypotheses presented, even this result would provide important insights. For example, a lack of significance in H5 would imply that the pro-automation environment in India (i.e. Digital India, Make in India policies) had been successful in reducing the size-related disparity seen elsewhere in the industry.

6. LIMITATIONS AND FUTURE SCOPE

6.1 Limitations

However, there are certain limitations associated with the design that need to be overcome as this research project advances from its theoretical framework into implementation. First, content-analysis scoring of disclosers incorporates a subjective element: even though a process of inter-rater reliability testing is suggested (Section 4.4), it is inevitable that some subjectivity will remain and different coding teams following the same criteria can yield somewhat different DAI scores. Moreover, secondary disclosure information may underestimate the level of automation activity that the company chooses not to disclose because of competitive concerns, or overestimate this level in cases when disclosure takes on more of a marketing/investor communications role than that of mere information provision; in such case, DAI might tend to reflect the quality of firms' investor communication practices rather than their automation capabilities. The use of purposive rather than random sampling of 30-50 firms creates generalizability problems to the larger population of Indian companies outside automation-oriented industries, and a six-year time horizon of the study (2020-2025) includes the period of the COVID-19 disruption that needs to be accounted for.

The other limitation is related to possible endogeneity whereby companies which are operationally efficient and those which have easier access to capital are more likely to automate their operations, making it possible for reverse causation between OE and DAI that cannot be sorted out by the usual fixed-effect panel estimation approach. Extensions such as instrumental variable or dynamic GMM estimations can be attempted once the baseline data set has been established, although such methods have their own limitations.

6.2 Future Research Directions

There are many ways future research can further develop and build upon the model. First, extending the sample to service industry companies and financial sector companies would help determine whether the relationship is specific to process-driven and asset-intensive industries, in which efficiency improvement through automation may take place through different mechanisms. Second, adding a lagged-effects specification – determining whether the DAI in year t predicts the OE in years t+1 and/or t+2 rather than just at a contemporaneous level – will allow distinguishing between the amount of time it takes for an automation-related investment to bear fruit and a mere contemporaneous correlation, thereby partially addressing the endogeneity issue mentioned earlier. Third, comparing the results obtained for India with those observed in other emerging countries that have undergone similar transitions into Industry 4.0 – say, Indonesia, Vietnam or other manufacturing countries in ASEAN region where moderation effect of firm size on digital transformation has already been empirically tested will help to determine whether the framework proposed here is specific for India or a common phenomenon among emerging countries.

7. CONCLUSIONS

Digital automation technology is transforming business operations practices in India, yet the processes that make the connection between automation disclosure and efficiency improvements testable through objective data have not been examined. In this study, a mediated-moderated model is proposed wherein IT Investment Intensity acts as a mediator and Firm Size acts as a moderator in the relationship between a Disclosure-based Digital Automation Index and Operational Efficiency in listed Indian firms. Based on the Resource-based View and Dynamic Capabilities theories, and empirical studies on digital transformation, value of IT and moderation by firm size, the model provides a theoretically sound and empirically testable explanation of how firms translate automation into efficiency improvement better than others.

In defining five hypothesis statements, proposing a nine-step panel-data empirical approach, and providing an index-construction process that can be replicated easily along with a reliable approach to testing, the paper presents a methodology for future secondary data-based study of the digital transformation process of emerging economies, identifying in advance the particular data availability concerns that need to be dealt with prior to estimating the proposed model. With the application of the proposed framework based on primary data on disclosures and finances, it is anticipated that theoretically motivated and practically useful evidence about the benefits of digital automation investments will emerge in case of Indian firms.

On a broader level, the theory is useful in establishing research designs within a growing body of research literature on digital automation not as one-dimensional, always-positive phenomenon, but as a means, whose value relies on other investments. Within the context of the Indian industries' ongoing rapid yet uneven adoption of Industry 4.0 (CII, 2025; EY India, 2025), research designs able to differentiate between revealed intention and the actual capabilities of a firm and able to single out those firms with structures enabling them to utilize automation to improve their efficiency will be very helpful for managers deciding where to invest their limited budgets, for investors valuing the payoffs of digital strategies, and for policymakers developing new initiatives to support manufacturing digitization. The present study helps to make such a differentiation clear and empirically observable and replicable through publicly available data.

ACKNOWLEDGEMENT

Firstly, I would like to thank our respected Principal, Dr. B. G. Prasad, Principal, Dayananda Sagar College of Engineering, Bengaluru, for giving me an opportunity to conduct this research study.

I would like to thank our respected Head of the Department, Dr. K. G. Hemalatha, Professor and Head, Department of Management Studies, Dayananda Sagar College of Engineering, Bengaluru, for her continuous motivation and encouragement during this academic exercise.

I would like to extend my deep sense of gratitude to my research guide, Dr. Vaishnavi Balaji, Professor, Department of Management Studies, Dayananda Sagar College of Engineering, Bengaluru, for her continuous support, guidance, and motivation during the preparation of this research manuscript. She played a vital role in the successful conduct of this research project.

Lastly, I would like to thank my dear parents and friends for their continuous moral and intellectual support, encouragement, and motivation during this research work.

REFERENCES

- Arshad, F. M., Anderson, S. W., Dekker, H., & Aguilar, O. (2025). Making business processes intelligent: Complementarities of combining robotic process automation and AI technologies. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5225098

- Confederation of Indian Industry. (2025). Industry 4.0 adoption: Paving the way for Indian manufacturing. CII Blog. https://ciiblog.in/industry-4-0-adoption-paving-the-way-for-indian-manufacturing/

- EY India. (2025). Digital transformation: India's journey to Industry 4.0 excellence. Ernst & Young. https://www.ey.com/en_in/insights/technology
- Ghofar, A., Kusumadewi, A. W., & Widiastutik, R. N. (2025). Does firm size strengthen the relationship between digital transformation and capital structure? A case in ASEAN nations. Cogent Business & Management, 12(1), Article 2570503. https://doi.org/10.1080/23311975.2025.2570503
- Harris, S. E., & Katz, J. L. (1991). Organizational performance and information technology investment intensity in the insurance industry. Organization Science, 2(3), 263–295.
- Hitt, L. M., & Brynjolfsson, E. (1996). Productivity, business profitability, and consumer surplus: Three different measures of information technology value. MIS Quarterly, 20(2), 121–143. https://doi.org/10.2307/249475
- Ilmudeen, A., & Bao, Y. (2019). Mediating role of managing information technology and its impact on firm performance: Insight from China (arXiv:1903.08934). arXiv. https://arxiv.org/abs/1903.08934
- Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2020). As cited in Valaskova, K., Nagy, M., & Juracka, D. (2025).
- Luo, X., & Yu, S.-C. (2022). The regulatory effect of firm size on digital transformation: An empirical study of pharmaceutical companies in China. Mathematical Problems in Engineering, 2022, Article 7731174. https://doi.org/10.1155/2022/7731174
- NASSCOM, & Capgemini. (2022). India Industry 4.0 adoption: A case to mature manufacturing digitalization by 2025. NASSCOM. https://community.nasscom.in/communities/industry-40
- Valaskova, K., Nagy, M., & Juracka, D. (2025). Digital transformation and financial performance: An empirical analysis of strategic alignment in the digital age. Journal of Enterprising Communities: People and Places in the Global Economy, 19(5), 1178–1205. https://doi.org/10.1108/JEC-11-2024-0241
- Zhou, J., Mei, J., & Naseem, A. (2025). Supply chain integration and innovation performance of manufacturing firms: The moderating role of research and development investment intensity. PLOS ONE, 20(2), Article e0316251. https://doi.org/10.1371/journal.pone.0316251

BIOGRAPHY

Deepashree P Kulkarni is an MBA student at Dayananda Sagar College of Engineering, Dept of Management Studies, Bangalore, specializing in Finance and Analytics with a strong interest in financial markets, data-driven decision-making, and sustainable investing. With experience in content creation, marketing strategy, and analytical research, Deepashree focuses on exploring the intersection of technology, finance, and global economic trends. Her academic work emphasizes practical and accessible approaches to complex financial problems, particularly in areas such as ESG investing, risk analysis, and predictive analytics. Deepashree aims to contribute to research that bridges theory and real-world application, supporting better strategic decision-making in dynamic and uncertain business environments.