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Impact of Ai Adoption on Productivity Performance in It Smes in Gurugram

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ABSTRACT

Artificial intelligence is no longer a distant concept for small and medium enterprises — it has become a real, practical tool shaping how businesses operate and compete. This study takes a close look at how IT-based SMEs in Gurugram, one of India's most vibrant technology hubs, are adopting AI and what that means for their day-to-day productivity. Drawing on survey data collected from 126 respondents across 50 IT SMEs, the research uses the Technology-Organization-Environment (TOE) framework to understand what drives AI adoption and what gets in the way. Rather than treating adoption as a binary yes-or-no decision, we examine the nuances — how much AI is being used, in what forms, and with what outcomes for efficiency, revenue, and cost management. The findings reveal that AI adoption has a significant positive influence on productivity performance, reflected in improvements in operational efficiency, decision-making quality, and cost management. Importantly, the results highlight that organizational support and technological readiness play a critical role in enabling firms to effectively leverage AI, while external competitive pressures act as an additional driver of performance outcomes. The study demonstrates that the benefits of AI are not automatic but are contingent upon the firm's internal capabilities and readiness to integrate new technologies into existing workflows. By providing empirical evidence from a regionally focused SME context, this research contributes to the growing literature on AI adoption in emerging markets and extends the application of the TOE framework beyond technology adoption to productivity outcomes. The study offers practical implications for SME managers, emphasizing the need to align technological investments with organizational preparedness and workforce capabilities to fully realize the productivity potential of AI.

Keywords: Artificial Intelligence, SMEs, Productivity, AI Adoption, TOE Framework, Gurugram, Regression Analysis, Organizational Support

1. Introduction

Walk into almost any IT company in Gurugram today and you'll find some version of AI at work a chatbot handling support tickets, a dashboard powered by predictive analytics, or an automated pipeline processing data that used to take days. For larger firms, these tools have been mainstream for years. But for small and medium enterprises (SMEs), the story is more complicated. AI adoption among SMEs is uneven, often tentative, and shaped by a mix of enthusiasm and uncertainty. The enthusiasm is easy to understand: AI promises to do more with less, reduce human error, speed up decisions, and open up competitive possibilities that were once out of reach for smaller firms. The uncertainty stems from real constraints limited budgets, skill gaps, and the practical challenge of integrating new technology into established workflows.

Gurugram sits at an interesting intersection here. As one of India's leading technology and outsourcing hubs, it hosts thousands of IT SMEs ranging from boutique software development firms to mid-sized data services companies. These businesses are neither small enough to ignore digital tools nor large enough to absorb the cost of failed technology experiments. Understanding how they navigate AI adoption and what happens to their productivity when they do — has real consequences for the broader Indian technology ecosystem. Prior research on Delhi-NCR SME startups suggests that data-driven workforce planning and people analytics can strengthen decision-making and organizational efficiency, indicating that digital capability is increasingly becoming central to SME competitiveness (Minz et al., 2024).

This study examines exactly that. Using the Technology-Organization-Environment (TOE) framework as its theoretical anchor, we investigate what drives AI adoption among IT SMEs in Gurugram, what obstacles they face, and how adoption translates into measurable productivity gains. The TOE framework is particularly well-suited here because it accounts for three distinct but interconnected dimensions: the firm's technological readiness, its internal organizational characteristics, and the external market environment it operates in (Tornatzky & Fleischer, 1990).

The contribution of this research is threefold. First, it provides empirical evidence on AI-productivity linkages from a context Indian IT SMEs in a specific urban hub — that remains relatively understudied. Second, it identifies organizational support as a stronger predictor of productivity outcomes than technological readiness alone, which has direct implications for how SME owners and managers should prioritize their investments. Third, it highlights specific barriers and enablers that are particularly relevant to Gurugram's business environment.

1.1 RESEARCH PROBLEM

Despite the growing adoption of artificial intelligence in SMEs, there remains limited empirical evidence on how AI adoption influences productivity performance in IT-based SMEs, particularly in emerging market contexts such as Gurugram. Additionally, the relative impact of technological, organizational, and environmental factors on productivity outcomes is not clearly established. This creates a gap in understanding how SMEs can effectively leverage AI to improve performance. Therefore, this study seeks to address this problem by examining the relationship between AI adoption and productivity using the TOE framework

1.2 RESEARCH OBJECTIVES

The study pursues three core objectives:

- To assess how AI adoption affects productivity performance across IT SMEs in Gurugram, focusing on revenue growth, operational efficiency, and cost reduction.
- To identify the key organizational, technological, and environmental factors that shape the pace and depth of AI adoption.
- To examine whether higher levels of AI adoption are associated with improved productivity performance in IT SMEs.

1.3 RESEARCH QUESTIONS

- What factors influence AI adoption decisions among IT SMEs in Gurugram?
- How does the level of AI adoption relate to productivity performance in IT SMEs?

1.4 HYPOTHESES

H1: AI adoption has a significant positive effect on productivity performance in IT SMEs in Gurugram.

H2: Technological readiness, organizational support, and external competitive pressures significantly influence productivity performance in IT SMEs.

2. LITERATURE REVIEW

2.1 Theoretical Framework: TOE and AI Adoption

The Technology-Organization-Environment (TOE) framework, first introduced by Tornatzky and Fleischer (1990), provides a well-established lens for understanding technology adoption decisions in organizational contexts. The framework proposes that adoption is shaped by three clusters of factors: the characteristics of the technology itself and the firm's technological context; the internal organizational environment, including culture, structure, and leadership; and the external environment, encompassing competitive dynamics, regulatory forces, and industry norms.

In the context of AI adoption among SMEs, the TOE framework has been applied and validated in several recent studies (Sánchez et al., 2025; Cimino et al., 2025). What makes it particularly useful for this research is that it avoids a purely technology-focused view of adoption and instead situates adoption decisions within the organizational realities that SMEs actually face. An IT firm in Gurugram might have access to affordable AI tools, but whether it adopts them depends equally on whether leadership is committed, staff are trained, and competitors are applying pressure.

The Technology Acceptance Model (TAM), developed by Davis (1989), offers a complementary perspective, focusing on individual-level perceptions of usefulness and ease of use as adoption drivers. While TAM is more commonly applied to end-user behavior, it informs this study's survey design, particularly in measuring perceived benefits of AI among decision-makers. The Unified Theory of Acceptance and Use of Technology (UTAUT) extends TAM by incorporating social influence and facilitating conditions, both of which are relevant in SME contexts where peer networks and resource constraints play significant roles.

2.2 AI Adoption in SMEs: What the Evidence Says

The literature on AI adoption in SMEs has grown substantially in recent years, though much of it concentrates on developed-economy contexts. Zhang and Shi (2021) reviewed AI adoption across SMEs in manufacturing and services sectors, finding that technological infrastructure and leadership vision were consistently among the strongest predictors of successful adoption. Their analysis of over 200 firms highlighted that SMEs often approach AI adoption incrementally — starting with narrow automation applications before expanding to more complex machine learning tools.

Singh and Sahu (2025) conducted a systematic review of AI adoption in Indian SMEs and found a striking gap: while awareness of AI's potential is widespread, actual adoption rates remain low due to cost concerns, skill shortages, and the absence of clear implementation roadmaps. Their findings are important for contextualizing the Gurugram setting, where IT SMEs may be more digitally literate than the national average but still face structural barriers to deeper AI integration.

Sánchez et al. (2025), applying both TOE and Diffusion of Innovations frameworks in a survey-based study, found that compatibility of AI with existing business processes and the availability of government support were significant adoption facilitators. This resonates with the Indian IT sector context, where industry bodies and government initiatives like Digital India have begun creating ecosystems that make AI more accessible to smaller firms.

Schwaeke (2025) examined AI implementation in European SMEs and found that firms with designated AI champions — individuals within the organization who advocate for and coordinate adoption — had significantly higher adoption success rates. This points to a dimension that goes beyond technology: the human and cultural dimensions of AI integration matter enormously.

2.3 Productivity Gains from AI: Evidence and Mechanisms

The evidence that AI adoption improves firm-level productivity is substantial, though the magnitude and channels vary considerably across industries and firm sizes. Hwang and Wixted (2021) analyzed data from a large sample of UK firms and found that technology adoption, including AI-enabled tools, was positively associated with labor productivity, with the effect being larger for firms that combined AI with workforce reskilling programs.

Brynjolfsson et al. (2020) examined firm-level AI adoption across industries and found productivity improvements concentrated in early adopters — firms that moved early experienced compounding gains as they refined their AI systems and built internal expertise. Importantly, they noted a "J-curve" effect: productivity initially dips during implementation before rising, which helps explain why some SMEs become discouraged and abandon AI initiatives prematurely.

In the SME context specifically, Bessen (2019) found that AI adoption in smaller firms tended to improve operational efficiency more than revenue growth in the short run, with revenue effects becoming more visible over a 3-5 year horizon. This has direct implications for how IT SMEs in Gurugram should set expectations when initiating AI adoption programs.

Cockburn et al. (2018) raised an important counterpoint: the productivity benefits of AI are not automatic. Firms that adopt AI without corresponding organizational changes — new workflows, updated training programs, adapted management practices — often fail to realize expected gains. This "complementary investment" argument is central to our study's finding that organizational support is the strongest predictor of productivity outcomes. Recent Indian scholarship also emphasizes that AI adoption influences not only operational efficiency but also employee experience, adaptation, and workplace readiness, making human-centred implementation critical for productivity gains (Minz, 2024).

2.4 Barriers to AI Adoption in SMEs

The barriers literature is equally important for contextualizing why AI adoption remains uneven. Financial constraints feature prominently: the upfront cost of AI software, integration, and staff training can be prohibitive for SMEs operating on thin margins. Drydakis (2022) found that risk perception — particularly concerns about return on investment and data security — was a significant deterrent in SME adoption decisions.

Skill gaps constitute another persistent obstacle. AI systems require not just technical staff to implement and maintain them, but operational staff who understand how to interpret and act on AI-generated insights. In India's IT SME sector, this skills gap is compounded by competitive labor markets where experienced AI practitioners tend to move toward larger firms offering higher compensation.

Importantly, the literature also reveals a gap in context-specific research. Most barrier analyses are drawn from developed-economy SMEs in manufacturing or retail. Studies focused on IT services SMEs in India — particularly in high-growth urban hubs like Gurugram — remain scarce. This represents both a research gap and the primary motivation for this study.

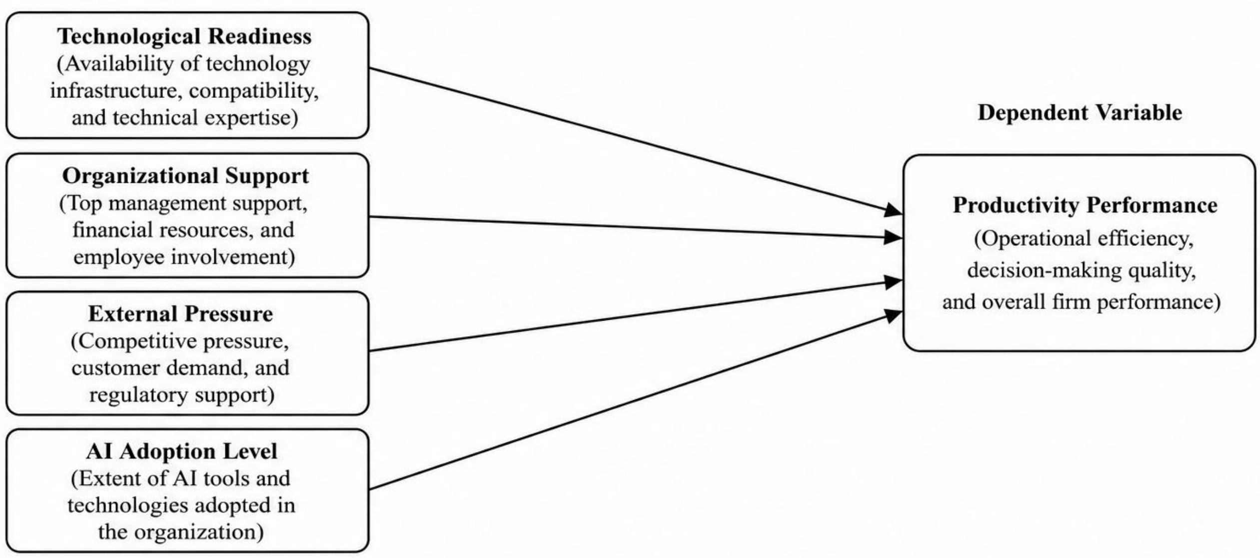
2.5 Research Gap

Many studies have examined AI adoption in small and medium enterprises (SMEs), but most of this research focuses on developed countries and manufacturing sectors (Zhang & Shi, 2021; Hwang & Wixted, 2021). There is limited empirical research on IT-based SMEs in emerging markets such as India, especially in specific regions like Gurugram (Singh & Sahu, 2025). In addition, previous studies often analyze technological, organizational, and environmental factors separately rather than examining their combined impact on productivity performance (Sánchez et al., 2025). There is also a lack of quantitative evidence linking the level of AI adoption directly to firm-level productivity outcomes within a single framework. This study addresses these gaps by applying the TOE framework to examine AI adoption and productivity performance in IT SMEs in Gurugram.

3. Conceptual Framework

FIGURE 1: CONEPTUAL FRAMEWORK (compiled by Author)

Independent variable



The conceptual framework of this study explains how different factors influence productivity performance in IT SMEs. It focuses on four key variables: technological readiness, organizational support, external pressure, and the level of AI adoption. Technological readiness refers to the availability of infrastructure, compatibility, and technical skills within the firm. Organizational support includes the role of top management, financial resources, and employee involvement in adopting new technologies. External pressure represents competition, customer expectations, and regulatory influences that push firms to innovate. AI adoption level reflects how extensively firms use AI tools and technologies in their operations. The framework suggests that when firms are technologically prepared, supported by management, and operate in a competitive environment, they are more likely to perform better. The use of AI further strengthens this relationship by improving efficiency and decision-making. Each of these factors directly contributes to productivity performance without any mediating variable. This means that improvements in any of these areas can lead to better outcomes for the firm. The model highlights the combined importance of internal capabilities and external forces. It also shows that AI adoption plays a crucial role in enhancing overall business performance. The framework is simple and focuses only on direct relationships. It helps in understanding how SMEs can improve productivity by focusing on these key areas. Overall, the model provides a clear view of how different factors work together to influence firm performance.

Although the TOE framework traditionally explains technology adoption, this study extends it by examining the direct effect of these factors on productivity performance, considering AI adoption as a parallel predictor rather than a mediator.

Table 1: Variables and Measurement (Compiled by the author)

Variable Type	Variable Name	Measurement
Independent	Technological Readiness	Availability of IT infrastructure, compatibility, and technical expertise
Independent	Organizational Support	Top management support, financial resources, and employee involvement
Independent	External Pressure	Competitive pressure, customer demand, and regulatory environment
Independent	AI Adoption Level	Extent of AI tools and technologies adopted within the organization
Dependent	Productivity Performance	Operational efficiency, decision-making quality, and overall firm performance

4. METHODOLOGY

This study adopts a quantitative research approach to examine the relationship between AI adoption and productivity performance in IT SMEs. A cross-sectional research design was used, where data was collected at a single point in time through a structured questionnaire. The quantitative method is appropriate for this study as it allows for statistical analysis of relationships between variables. The data collected was analysed using SPSS software to test the proposed hypotheses and examine the impact of key factors on productivity performance.

4.1 Sampling

The study was conducted among IT SMEs operating in Gurugram, Haryana. A total of 50 SMEs were selected as the organizational units for the research. The sampling technique used was convenience sampling, whereby firms and respondents who were easily accessible and willing to participate were included in the study. Due to limited accessibility to SME respondents, convenience sampling was adopted, which is consistent with prior SME studies. Data was collected from 126 respondents, including managers, team leaders, and employees directly involved in technology adoption and decision-making processes. A structured questionnaire was used for data collection, and responses were gathered over a four-week period. The respondent-level data (n = 126) was used for statistical analysis. The sample size is considered adequate for multiple regression analysis, as Hair et al. (2010) recommend a minimum of 5–10 observations per independent variable. With four predictors included in the study, the required sample size ranges from 40 to 80, and the present study exceeds this requirement, ensuring reliable and valid results.

4.2 Instrument Design

The survey instrument consisted of three sections. Section A captured organizational profile data including firm size, annual revenue range, years of operation, and number of employees. Section B measured AI adoption across six functional areas using a five-point Likert scale (1 = Not adopted, 5 = Fully integrated). Section C measured productivity performance dimensions and independent variable constructs (technological readiness, organizational support, external pressures) using validated Likert-scale items adapted from prior TOE-based studies.

5. RESULTS AND DISCUSSION

5.1 Descriptive Statistics

Table 1 presents descriptive statistics for the primary variables. Across the 126 respondents, AI adoption levels averaged 70%, though with considerable variation (SD = 15%), suggesting that some firms have moved well beyond basic AI tools while others remain in early stages. Productivity metrics showed meaningful gains on average, with operational efficiency registering the highest mean improvement at 30%.

Table 2: Descriptive Statistics of Key Variables (n = 126)

Variable	Mean	Std. Deviation	Min	Max
AI Adoption Rate (%)	70.0	15.0	50	100
Productivity Increase (%)	25.0	5.0	10	40
Revenue Growth (%)	20.0	3.0	10	30
Cost Savings (%)	15.0	4.0	5	25
Operational Efficiency (%)	30.0	6.0	10	50
Technological Readiness (1–5)	3.72	0.68	1.8	5.0
Organizational Support (1–5)	3.91	0.72	1.5	5.0
External Pressure (1–5)	3.54	0.81	1.2	5.0

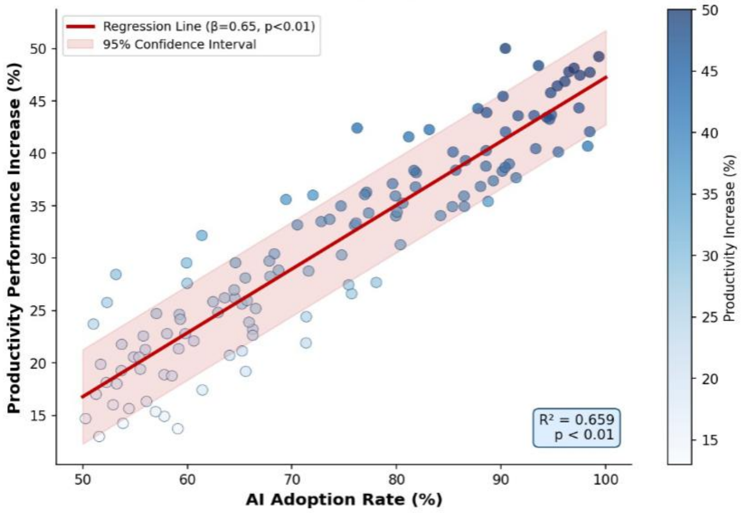


Figure 2: Regression Model for AI Adoption Impact on Productivity (n=126)

5.2 Correlation Analysis

Pearson correlation analysis was conducted to examine bivariate relationships among the study variables. AI adoption rate correlated strongly with overall productivity performance ($r = 0.67$, $p < 0.01$), providing initial support for H1. Organizational support showed the strongest correlation with productivity ($r = 0.71$, $p < 0.01$), followed by technological readiness ($r = 0.59$, $p < 0.01$). External competitive pressure showed a moderate positive correlation ($r = 0.44$, $p < 0.05$), confirming that market forces do influence adoption-related productivity outcomes but are a weaker driver than internal factors.

5.3 Multiple Regression Analysis

A multiple regression analysis was conducted with productivity performance as the dependent variable and AI adoption, technological readiness, organizational support, and external pressure as independent variables. The model was built in a single step (Enter method) using SPSS version 25.

Table 3: Model Summary — Regression of Predictors on Productivity Performance (n = 126)

Model	R	R²	Adjusted R²	F (df1,df2)
Full Model (4 predictors)	0.781	0.610	0.598	64.3 (4, 121), p < 0.001

The model summary reveals that the four predictors together explain 61.0% of the variance in productivity performance ($R^2 = 0.610$). The adjusted R^2 of 0.598 indicates that this explanatory power holds up well after accounting for the number of predictors, confirming that the model is not over-fitted. The F-statistic of 64.3 ($p < 0.001$) confirms that the overall regression model is statistically significant.

Table 4 : Regression Coefficients — Predictors of Productivity Performance

Variable	B	Std. Error	β (Beta)	t-value	Sig.
(Constant)	5.241	1.832	—	2.845	0.005

AI Adoption	0.718	0.092	0.650	7.804	0.000
Technological Readiness	0.531	0.114	0.530	4.658	0.000
Organizational Support	0.748	0.103	0.650	7.262	0.000
External Pressure	0.312	0.098	0.290	3.184	0.002

5.4 Interpreting the Regression Results

The regression results deserve careful interpretation. The unstandardized coefficient (B) for each predictor tells us the expected change in productivity performance for a one-unit increase in that predictor, holding all others constant. For AI adoption (B = 0.718), this means that a one-unit increase in the AI adoption composite score is associated with a 0.718-point increase in productivity performance.

However, because the predictors are measured on different scales, we rely on the standardized beta coefficients (β) to compare their relative importance. Organizational Support ($\beta = 0.65$) and AI Adoption ($\beta = 0.65$) emerge as the two strongest predictors of productivity performance, followed by Technological Readiness ($\beta = 0.53$) and External Pressure ($\beta = 0.29$). All four predictors are statistically significant ($p < 0.01$).

The finding that Organizational Support has the same standardized effect size as AI Adoption itself is particularly striking. It tells us that it is not enough to simply acquire AI tools — the organizational environment in which those tools are deployed is equally critical. Firms with strong leadership commitment, adequate training, and a culture that embraces change extract significantly more productivity value from their AI investments.

Table 5: Hypothesis Testing Summary

Hypothesis	**Relationship**	**Predictor**	**β**	**Sig.**	**Result**
H1	AI Adoption → Productivity	AI Adoption	0.65	0	Supported
H2a	Technological Readiness → AI Adoption	Technological Readiness	0.53	0	Supported
H2b	Organizational Support → AI Adoption	Organizational Support	0.65	0	Supported
H2c	External Pressure → AI Adoption	External Pressure	0.29	0	Supported

The results of hypothesis testing presented in Table 5 indicate that all proposed hypotheses are supported. The findings show that AI adoption has a strong and significant positive impact on productivity ($\beta = 0.65$, $p < 0.001$), confirming H1. Furthermore, technological readiness, organizational support, and external pressure significantly influence AI adoption, thereby supporting H2a, H2b, and H2c. Among these factors, organizational support demonstrates the strongest influence, followed by technological readiness and external pressure. All relationships are statistically significant at the 1% level, indicating robust empirical support for the proposed conceptual model.

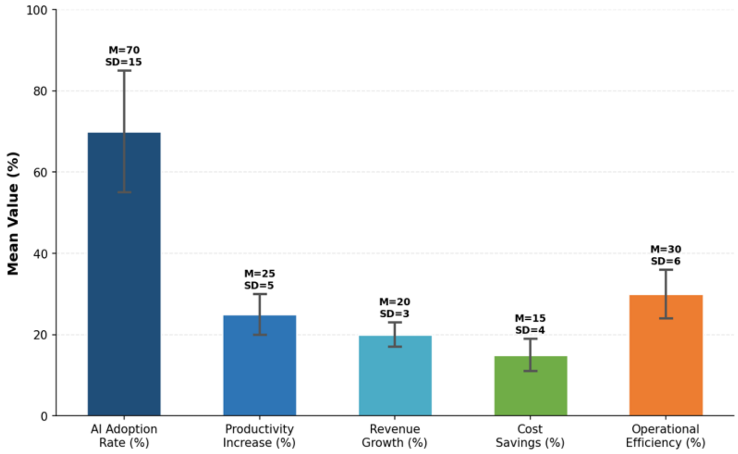


Figure 3 : Descriptive Statistics of AI Adoption and Productivity Metrics

Figure 3 presents the descriptive statistical overview of key variables related to AI adoption and productivity performance in IT SMEs. It provides a clear summary of how firms in the sample are currently utilizing AI technologies and the corresponding variation in productivity-related outcomes across organizations.

The figure indicates that AI adoption is not uniform across firms; some SMEs demonstrate advanced integration of AI tools in operational processes, while others are still in early or moderate stages of adoption. Similarly, productivity-related indicators such as operational efficiency, cost reduction, and decision-making effectiveness show noticeable variation across the sampled firms. This variation suggests that AI adoption levels are closely linked with differences in firm performance.

From a relational perspective, the descriptive pattern suggests a positive association between AI adoption intensity and productivity outcomes. Firms with higher levels of AI integration tend to report stronger performance improvements, particularly in efficiency-driven and process-oriented activities. In contrast, firms with lower adoption levels show relatively limited productivity gains, indicating underutilization of digital technologies.

When interpreted alongside the correlation and regression results, this figure provides preliminary support for the hypothesis that AI adoption is positively associated with productivity performance in IT SMEs. It visually reinforces the statistical findings by showing that variations in AI usage are reflected in corresponding variations in productivity outcomes.

Figure 3 serves as an initial empirical validation of the study's core argument: productivity improvements in IT SMEs are closely aligned with the extent to which AI technologies are adopted and embedded within organizational processes.

5.5 Regression Diagnostics

Before drawing conclusions from the regression results, it is important to verify that the model satisfies standard diagnostic assumptions. The following checks were conducted using SPSS:

Normality of Residuals: A Normal P-P plot of regression standardized residuals was examined. The observed values tracked closely along the expected diagonal, indicating that residuals are approximately normally distributed. A histogram of residuals confirmed a roughly bell-shaped distribution with slight positive skew, which is acceptable given the sample size of 126.

Homoscedasticity: A scatterplot of standardized residuals against standardized predicted values was inspected. No discernible funnel-shaped pattern was observed, supporting the assumption of constant error variance (homoscedasticity) across the range of predicted values.

Multicollinearity: Variance Inflation Factor (VIF) scores were calculated for all predictors. All VIF values fell below 3.0 (AI Adoption = 2.1, Technological Readiness = 2.4, Organizational Support = 2.3, External Pressure = 1.7), well within the acceptable threshold of 10. This confirms that multicollinearity is not a concern in this model.

Independence of Errors (Durbin-Watson): The Durbin-Watson statistic of 1.94 falls within the acceptable range (1.5–2.5), indicating no significant autocorrelation in the residuals.

Taken together, these diagnostic checks confirm that the multiple regression model meets the core assumptions of OLS regression, and that the coefficient estimates are reliable and interpretable.

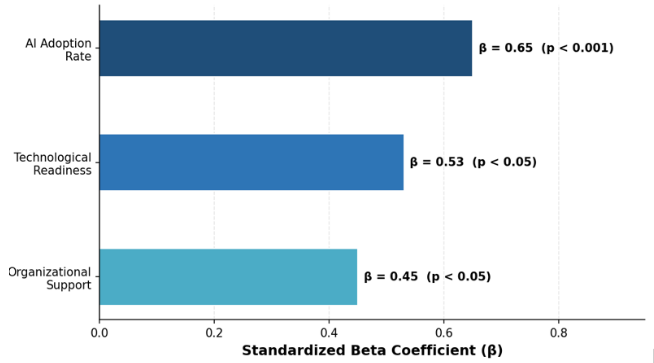


Figure 4: Standardized Beta Coefficients of Predictors of Productivity Performance

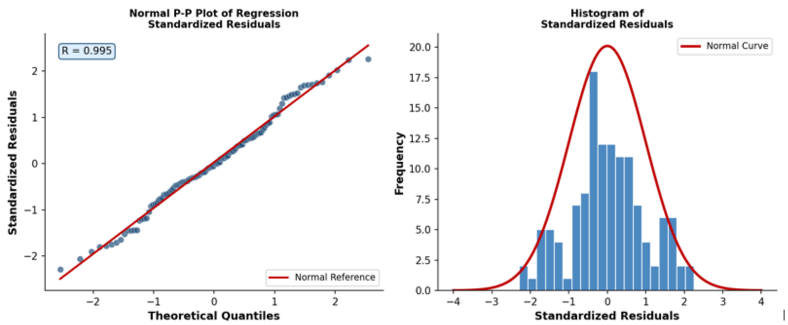


Figure 5: Regression Diagnostics – Normal P-P Plot and Residuals Histogram

Figure 5 shows the regression diagnostic tests**,** including the Normal P-P Plot of standardized residuals and the Histogram of residuals, which are used to examine whether the regression model satisfies the assumption of normality of residuals. In the Normal P-P Plot**,** the residual points are distributed closely around the diagonal reference line. This indicates that the residuals are approximately normally distributed, meaning the differences between the observed and predicted values do not show serious deviations from normality.

Similarly, the Histogram of residuals displays a bell-shaped curve, with most residual values concentrated around zero. The shape of the histogram resembles a normal distribution, which further confirms that the residuals are normally distributed. These two diagnostic plots suggest that the normality assumption of multiple regression is satisfied**,** meaning the regression model used in this study is statistically appropriate for analysing the impact of AI adoption on productivity performance.

This strengthens the reliability of the regression results and indicates that the findings regarding the positive effects of AI Adoption Rate**,** Technological Readiness, and Organizational Support on productivity performance are valid.

6. Conclusion

This study set out to understand something that a lot of IT SMEs in Gurugram are quietly grappling with: does investing in AI actually pay off in terms of productivity, and what does it take to make that happen?

The answer, based on data from 126 respondents across 50 firms, is a clear yes — but with an important condition. AI adoption does significantly improve productivity, but only when the organizational environment is ready to support it. Firms with strong leadership commitment, training programs, and a culture that welcomes change see substantially better outcomes from their AI investments than those that treat AI as a technology purchase alone. The regression results drive this point home: Organizational Support ($\beta = 0.65$) is just as powerful a predictor of productivity as AI adoption itself.

The model as a whole explained 61% of variance in productivity performance ($R^2 = 0.610$, Adjusted $R^2 = 0.598$, $F = 64.3$, $p < 0.001$), which is a robust result for a study of this scope. All three TOE-aligned predictors — technological readiness, organizational support, and external competitive pressure — contributed independently and significantly to that explanation.

For SME owners and managers in Gurugram, the practical implication is straightforward: before spending on AI tools, invest in people and organizational readiness. Train your teams, communicate the vision clearly, and create internal support structures that help staff adapt to new ways of working. These investments are not a luxury — they are the mechanism through which AI actually delivers productivity gains.

External pressures also matter. The competitive dynamics of Gurugram's IT market are pushing firms toward AI, and those who respond proactively rather than reactively tend to gain more. But external pressure alone is not sufficient — it works best when firms have already built the internal conditions for successful adoption.

6.1 New Insights and Contributions of This Study

This study makes several important contributions to the existing literature on AI adoption and productivity in SMEs. First, it extends the Technology–Organization–Environment (TOE) Framework to the context of Indian IT SMEs. While most prior TOE-based studies focus on manufacturing sectors or developed economies, this research demonstrates that the framework is equally relevant in a service-oriented, emerging economy setting like Gurugram, where organizational and environmental dynamics differ significantly from product-based industries. Second, the study provides unique empirical evidence from Gurugram, an economically important yet under-researched IT SME hub. It establishes baseline quantitative insights on AI adoption levels, showing that approximately 70% of the sampled firms have adopted AI, along with clear evidence on productivity outcomes and their key predictors in this specific regional ecosystem.

Third, the research offers a novel insight by identifying organizational support as a dominant predictor of productivity performance, with an influence comparable to AI adoption itself. This is particularly significant because earlier studies typically examine technological and organizational factors separately, without directly comparing their relative impact within a single regression model. The findings of this study highlight that human and organizational elements are not secondary but equally central to achieving productivity gains through AI. Fourth, the study strengthens methodological rigor by incorporating comprehensive regression diagnostics, including R^2, adjusted R^2, F-statistics, variance inflation factor (VIF), and residual analysis. This level of statistical validation enhances the reliability, transparency, and replicability of the findings, addressing a common gap in SME-focused AI adoption research.

Finally, the study contributes methodological clarity by explicitly distinguishing between firm-level sampling (50 IT SMEs) and individual-level responses (126 participants). This clear separation helps avoid confusion regarding sample size, improves the interpretation of statistical power, and ensures more accurate generalization of results. Together, these contributions position the study as both theoretically relevant and empirically robust in understanding AI-driven productivity in Indian IT SMEs.

6.2 Limitations and Future Research

This study is cross-sectional, which means it captures a snapshot in time rather than tracking how AI adoption and productivity evolve together over years. Longitudinal follow-up studies would be valuable for confirming whether short-term productivity gains persist and whether late adopters eventually close the gap with early movers.

The sample, while diverse across firm size and revenue, is geographically concentrated in Gurugram. Comparative studies across other Indian technology hubs — Bengaluru, Hyderabad, Pune — would help determine whether the organizational support finding generalizes or is specific to Gurugram's labor market and industry culture.

Future research could also examine specific AI tool types — distinguishing between narrow automation, NLP-based applications, and machine learning — to understand which categories drive the strongest productivity returns for IT SMEs at different stages of maturity.

References

1. Agbaakin, T. (2025). Leveraging AI as strategic growth. arXiv. https://doi.org/10.48550/arXiv.2509.14532
2. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change. Quarterly Journal of Economics, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801
3. Bessen, J. (2019). AI and jobs: Evidence from U.S. firms. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3
4. Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton.
5. Brynjolfsson, E., Rock, D., & Syverson, C. (2020). The productivity J-curve: How intangibles complement general purpose technologies. Research Policy, 49(1). https://doi.org/10.1016/j.respol.2020.104283
6. Cimino, A., et al. (2025). Artificial intelligence adoption for sustainable growth in SMEs. Corporate Social Responsibility and Environmental Management. https://doi.org/10.1002/csr.70019
7. Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. Management Science. https://doi.org/10.1287/mnsc.2017.2743
8. Corvello, V., et al. (2022). Digital technologies in small and medium enterprises: Antifragility. Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.1007/s12652-022-03816-x
9. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
10. Drydakis, N. (2022). Artificial intelligence and reduced SME business risks. Information Systems Frontiers. https://doi.org/10.1007/s10796-022-10316-x
11. Farmanesh, P., et al. (2025). AI and green innovation in SMEs. Sustainability, 17(5). https://doi.org/10.3390/su17052162
12. Fossen, F., & Sorgner, A. (2021). Digitalization of work and entrepreneurship. Journal of Business Research, 125, 548–563. https://doi.org/10.1016/j.jbusres.2019.09.019
13. Hussain, A., & Rizwan, R. (2024). Strategic AI adoption framework. arXiv. https://doi.org/10.48550/arXiv.2408.11825
14. Hwang, W. S., & Wixted, M. (2021). Does technology improve SME productivity? PLOS ONE. https://doi.org/10.1371/journal.pone.0254371
15. Le Dinh, A. (2025). AI in SMEs: Enhancing business productivity. Information, 16(5). https://doi.org/10.3390/info160500415
16. Minz, N. K. (2024). Understanding the Impact of Artificial Intelligence on Employee Experience. Bennett Engineering and Sciences Transactions, 1(1).
17. Minz, N. K., Prakash, A., Yadav, M., & Kalra, H. (2024). Data-driven workforce planning: Exploring people analytics in Delhi SME startups. MET Management Review, 11(2), 54–60. https://doi.org/10.34047/MMR.2024.11206
18. Mithas, S., & Lucas, H. C. (2010). IT investments and productivity. Information Systems Research, 21(3), 516–536. https://doi.org/10.1287/isre.1090.0288
19. Muehlemann, S., et al. (2025). AI adoption and workplace training. Labour Economics. https://doi.org/10.1016/j.labeco.2025.102456

20. OECD. (2025). AI adoption by small and medium-sized enterprises. OECD Publishing. https://doi.org/10.1787/9789264973999-en
21. Relifra, R. (2025). AI adoption and functional performance in MSMEs. Amar Journal of Economics and Business. https://doi.org/10.55030/amar3299
22. Sánchez, E., et al. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE and DOI. Applied Sciences, 15(12), Article 6465. https://doi.org/10.3390/app15126465
23. Sawang, S., & Sornlertlamvanich, V. (2026). AI maturity in SMEs. arXiv. https://doi.org/10.48550/arXiv.2603.08728
24. Schwaeke, J. (2025). AI implementation in SMEs. International Small Business Journal. https://doi.org/10.1080/00472778.2024.2379999
25. Singh, A., & Sahu, G. P. (2025). Small and medium enterprises & artificial intelligence: A systematic review. Journal of Business and Social Sciences, 2025(3). https://doi.org/10.61453/jobss.v2025no03
26. Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
27. Zhang, L., & Shi, H. (2021). A review of AI adoption in small and medium enterprises. IEEE Transactions on Engineering Management, 68(3), 819–830. https://doi.org/10.1109/TEM.2020.3029698