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Impact of Artificial Intelligence Adoption on Employee Productivity in SMEs

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Abstract: The adoption of Artificial Intelligence (AI) technologies is increasingly transforming the operations of small and medium-sized enterprises (SMEs), influencing employee productivity (EP) through automation, decision support, and adaptive learning systems. This paper investigates the multifaceted effects of AI adoption on employee productivity in SMEs, drawing insights from recent empirical and theoretical studies. The analysis explores both enablers and inhibitors of productivity, emphasizing the mediating roles of organizational culture, employee autonomy, and technostress management. Studies in the literature suggest that AI integration can significantly enhance EP when combined with ethical governance and supportive work environments. Conversely, unregulated AI deployment may induce objectification, job anxiety, and reduced engagement. To address these challenges, this paper proposes a conceptual framework linking AI-enabled process innovation, task redesign, and upskilling to sustained productivity gains. The findings highlight that SMEs should strategically align AI adoption with human-centric practices to ensure that productivity improvements are both measurable and sustainable.

Keywords: Artificial Intelligence, Employee Productivity, Small and Medium-sized Enterprises, Organizational Performance, Workplace Innovation.

1 INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force reshaping the global business landscape, offering organizations new opportunities to enhance operational efficiency, innovation, and decision-making quality. For small and medium-sized enterprises (SMEs), which constitute more than 90% of global businesses and contribute significantly to employment generation, AI adoption has the potential to unlock new levels of employee productivity (EP) and competitiveness [1]. However, the integration of AI into organizational workflows brings both opportunities and challenges that must be understood in a human-centered context.

Employee productivity in SMEs is influenced not only by technology adoption but also by cultural, managerial, and psychological factors [2]. While AI systems can automate routine tasks, optimize workflows, and assist in data-driven decision-making, their impact on human performance depends on how employees perceive and interact with these systems. Studies indicate that when AI tools complement rather than replace human labor, they can significantly enhance performance, reduce cognitive load, and improve creativity and decision speed [3], [4]. Conversely, excessive reliance on AI automation without sufficient human control can lead to employee disengagement, technostress, and diminished trust [5].

The level of AI readiness among SMEs remains uneven across industries and regions. Research by Gupta *et al.* [2] highlights that SMEs often face resource limitations, lack of technical expertise, and insufficient digital infrastructure, which impede effective AI integration. Kassa and Worku [1] argue that leadership support and organizational learning play crucial roles in realizing productivity gains from digital transformation. Moreover, Chen *et al.* [3] emphasize that aligning AI tools with employees' task requirements and autonomy can produce measurable improvements in output quality and efficiency.

From a behavioral perspective, the interaction between human employees and AI systems is shaped by perceived usefulness, perceived threat, and organizational support mechanisms [6]. Employees who feel empowered to use AI tools effectively tend to report higher job satisfaction and productivity, while those who fear replacement or surveillance exhibit resistance and stress. This duality underscores the importance of adopting a human–AI collaboration model, where AI is positioned as an augmentative partner rather than a substitute for human capability [7], [8].

AI's impact on productivity is also mediated by organizational processes such as task redesign, workflow integration, and continuous learning. Scholars note that SMEs adopting AI for process optimization experience faster turnaround times and improved output consistency, if training and knowledge-sharing mechanisms are in place [9], [10]. Ethical and governance aspects further influence productivity outcomes. Transparent AI policies and responsible data practices foster employee confidence and reduce anxiety related to fairness and job security [11]. Considering these findings, this paper examines the dynamic relationship between AI adoption and employee productivity in SMEs. It seeks to address the following research objectives:

1. To identify the key enablers and barriers influencing AI-driven productivity in SMEs.
2. To analyze how organizational culture, leadership, and employee attitudes mediate AI's productivity outcomes.

3. To develop a conceptual framework linking AI adoption strategies to sustained employee productivity and organizational growth.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature on AI adoption and employee productivity. Section 3 presents the proposed conceptual framework. Section 4 outlines the research methodology, while Section 5 discusses results and implications. Section 6 concludes with recommendations for SME managers and policymakers.

2 Literature Review

Artificial Intelligence (AI) adoption in small and medium-sized enterprises (SMEs) has become a defining factor of organizational competitiveness in the digital era. Prior research broadly categorizes the impact of AI adoption on employee productivity (EP) into three domains: (i) productivity enablers, (ii) productivity inhibitors, and (iii) mediating or moderating factors that determine the strength and direction of AI's influence on human performance.

2.1 AI Adoption as a Productivity Enabler

AI enhances productivity primarily by automating repetitive tasks, augmenting decision-making, and facilitating innovation. Studies reveal that AI integration reduces operational inefficiencies and improves employee performance when aligned with strategic goals and human resource development [1], [2]. Gupta *et al.* [2] observed that AI adoption improves decision quality, responsiveness, and output accuracy through data-driven insights. Similarly, Chen *et al.* [3] demonstrated that AI-augmented decision systems in manufacturing SMEs increased throughput and task precision while reducing manual error rates.

AI-driven tools such as intelligent process automation, predictive analytics, and natural language processing have been shown to significantly reduce employees' cognitive load, allowing them to focus on high-value creative and analytical tasks [4]. Eberhardt [7] further asserts that AI functions as a performance enhancer when viewed as a collaborative augmentation rather than a replacement for human intelligence. This perspective aligns with Das and Sheikh [8], who highlight that human-centric AI adoption improves psychological well-being, job satisfaction, and performance sustainability.

The productivity-enabling effects of AI are most evident in SMEs that integrate AI-enabled process reengineering and continuous upskilling programs [9], [10]. Kamara [9] found that AI deployment in workflow automation improved product quality consistency, while Thomas and Cruz [10] emphasized that digitally literate employees adapt more rapidly to AI-driven systems, thus maintaining competitive productivity levels. These findings collectively indicate that AI's role as a productivity driver depends heavily on alignment with organizational learning and innovation strategies.

2.2 AI Adoption as a Productivity Inhibitor

While AI can be transformative, its adoption can also generate adverse outcomes when inadequately managed. Technostress, job insecurity, and ethical ambiguity are among the most cited inhibitors of employee productivity in AI-integrated workplaces [5], [6]. Richter and Unger [5] found that employees exposed to high levels of automation anxiety and surveillance reported decreased job satisfaction and reduced motivation. The perception of being constantly evaluated by AI-based monitoring systems can erode trust and engagement, leading to performance deterioration.

Huang *et al.* [6] identified psychological adaptation challenges among SME employees transitioning to AI-supported environments, where uncertainty about AI's decision logic fosters resistance. Similar findings by Annamalai *et al.* [11] show that the absence of ethical transparency and clear communication in AI implementation leads to mistrust and moral fatigue, negatively affecting performance. Furthermore, SMEs with limited technical capacity often struggle to provide adequate training or change management support, compounding stress and productivity loss.

Another inhibitory factor is skill obsolescence. As AI automates knowledge-intensive tasks, employees lacking digital competencies face role redundancy or reduced task significance [1]. This misalignment between human capabilities and AI functionalities contributes to perceived inequity and diminished intrinsic motivation. Consequently, AI's productivity benefits cannot be generalized without considering context-specific organizational and human factors.

2.3 Mediating and Moderating Factors Influencing Productivity Outcomes

A growing body of literature emphasizes that AI's impact on productivity is not direct, but mediated by organizational, individual, and technological variables [2], [3], [8]. Among these, organizational culture and leadership orientation are key determinants. Kassa and Worku [1] observed that transformational leadership fosters trust and collaboration in AI adoption, enabling employees to perceive technology as an enabler rather than a threat. Conversely, rigid hierarchical cultures hinder adaptation and exacerbate resistance.

Employee autonomy also moderates the AI-productivity relationship. Chen *et al.* [3] showed that when employees retain decision-making control in AI-augmented environments, their productivity levels rise significantly. Similarly, Eberhardt [7] found that human–AI collaboration thrives under decentralized structures that encourage experimentation and shared accountability. Technological readiness acts as both a prerequisite and a moderating condition. Gupta *et al.* [2] highlighted that AI readiness—defined by digital infrastructure, data governance, and skill availability—directly influences productivity outcomes. SMEs with low readiness experience delayed implementation and inefficient utilization of AI tools. Ethical governance, as discussed by Annamalai *et al.* [11], further mediates this relationship by enhancing transparency, ensuring data protection, and improving employees' confidence in AI systems.

Continuous learning ecosystems represent another critical mediator. Thomas and Cruz [10] demonstrated that SMEs incorporating digital learning programs into their AI strategies experienced steady productivity improvements due to enhanced adaptability and technical competence. Das and Sheikh [8] support this view, emphasizing that training and ethical orientation mitigate technostress while reinforcing human–AI trust.

2.4 Synthesis of the Literature

The reviewed literature indicates that AI's impact on employee productivity is multidimensional, shaped by both technical and human factors. When integrated responsibly—supported by ethical governance, transparent communication, and skill development—AI acts as a catalyst for productivity. However, unmanaged AI adoption risks inducing job anxiety, technostress, and resistance, especially in resource-constrained SMEs. The interplay of AI capability, organizational culture, leadership style, and employee adaptability determines whether AI ultimately enhances or diminishes productivity. This synthesis underscores the need for a holistic conceptual framework that integrates technological, human, and organizational perspectives to explain how AI adoption influences employee productivity. The next section (Section 3) presents such a framework, designed to capture the dynamic interactions among these factors within the SME context.

3 CONCEPTUAL FRAMEWORK

The reviewed literature establishes that the relationship between Artificial Intelligence (AI) adoption and employee productivity (EP) in small and medium-sized enterprises (SMEs) is complex, multidirectional, and influenced by several organizational and individual-level variables. This section proposes a conceptual framework that synthesizes these variables into an integrated model explaining how AI adoption affects employee productivity through mediating and moderating mechanisms.

3.1 Framework Overview

The proposed framework (Fig. 1) is built upon three foundational premises:

1. AI as a Capability Driver: AI technologies enhance employee productivity by automating routine processes, improving decision quality, and enabling intelligent support systems [2], [3], [4].
2. Human–Organizational Mediation: The effectiveness of AI depends on how employees interact with these systems, shaped by organizational culture, leadership, autonomy, and ethical environment [1], [7], [8], [11].
3. Feedback and Adaptation: Productivity outcomes further influence future AI adoption and digital learning, forming a feedback loop that strengthens organizational adaptability and competitiveness [9], [10].

3.2 Components of the Framework

(a) AI Adoption

AI adoption refers to the integration of intelligent technologies—such as predictive analytics, machine learning, and process automation—into core SME operations. The extent and maturity of AI adoption determine its potential to drive innovation and performance [2]. SMEs with high AI readiness and adequate digital infrastructure tend to experience greater productivity improvements than those with limited resources [1].

(b) Mediating Variables

Several mediating factors bridge the link between AI adoption and employee productivity:

1. Organizational Culture and Leadership: Transformational and participative leadership styles create trust and openness toward AI technologies. Supportive cultures encourage experimentation, reduce fear of failure, and promote AI-enabled learning [1], [7].
2. Employee Autonomy and Skill Development: When employees maintain control over AI-assisted decisions and have access to continuous learning opportunities, AI's benefits amplify [3], [8], [10]. Autonomy fosters ownership, accountability, and creative engagement, leading to sustained performance improvements.

3. Technostress Management: Excessive automation and AI-driven surveillance may cause anxiety, overload, or resistance [5], [6]. Effective stress mitigation—through transparent communication, ergonomic digital tools, and mental health support—ensures a smoother adoption process and stable productivity levels.
4. Ethical and Governance Practices: Ethical transparency, fairness in AI decisions, and privacy protection increase employees' trust and willingness to engage with intelligent systems [11]. These factors reduce cognitive dissonance and improve overall performance satisfaction.

(c) Employee Productivity (EP)

Employee productivity represents the measurable output or efficiency achieved per employee relative to effort, time, or resources. AI adoption influences EP through process optimization, redundancy reduction, and support for analytical or creative tasks [2], [4], [9]. However, productivity gains are contingent on successful mediation by cultural and individual factors.

(d) Feedback Mechanism

The model incorporates a **feedback loop** where enhanced productivity and employee adaptability strengthen AI capability utilization. Successful implementation leads to greater organizational learning and readiness, which in turn reinforces future AI adoption [10]. Conversely, negative experiences—such as high technostress or ethical conflicts—may reduce willingness to use AI tools, weakening the cycle.

3.3 Theoretical Underpinning

This framework draws upon three theoretical perspectives:

1. Socio-Technical Systems Theory (STS): This theory emphasizes the joint optimization of social and technical subsystems within organizations. AI must be integrated not merely as a technical innovation but as part of a socio-organizational ecosystem that values employee input and adaptability [6].
2. Job Demands–Resources (JD-R) Model: AI reduces job demands (e.g., repetitive tasks) while providing resources (e.g., decision support). However, if AI increases cognitive load or stress, its benefits may be offset. Proper resource balancing is therefore crucial [5], [8].
3. Human–AI Collaboration Theory: As proposed by Eberhardt [7] and Das and Sheikh [8], AI should augment human capabilities, not replace them. The synergy between algorithmic intelligence and human judgment leads to superior productivity outcomes.

3.4 Conceptual Model Description

The conceptual framework shown in Fig. 1 posits that:

- AI Adoption directly influences Employee Productivity.
- The strength of this relationship is mediated by Organizational Culture, Employee Autonomy, Technostress Management, and Ethical Governance.
- Continuous Learning and Feedback Mechanisms sustain productivity gains by improving AI utilization and readiness.
- Ethical and Human-centric Implementation acts as a stabilizing factor, ensuring that AI adoption remains productive and psychologically sustainable.

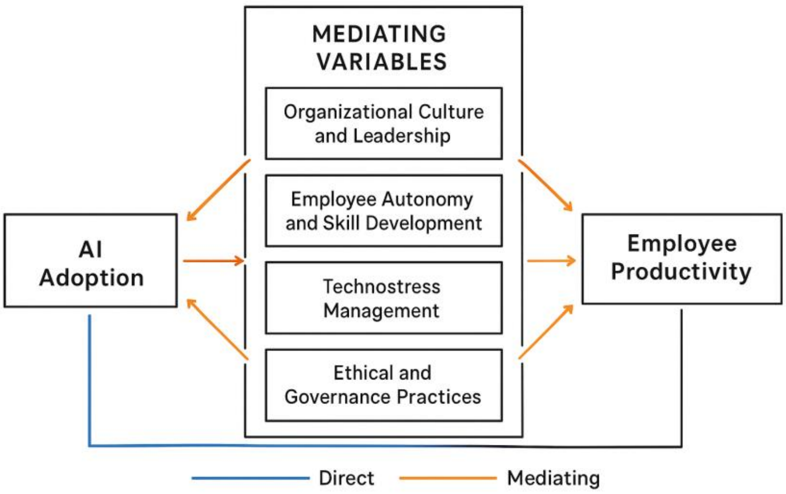

Fig. 1. Conceptual Framework of AI adoption and Employee Productivity in SMEs

4 Research Methodology

4.1 Research Design

This study adopts a quantitative, cross-sectional research design aimed at empirically validating the conceptual relationships proposed in Section 3. The research investigates how AI adoption influences employee productivity in small and medium-sized enterprises (SMEs) through mediating organizational and behavioral factors. This design aligns with prior quantitative analyses in technology adoption and productivity studies [1], [2], [3], allowing the collection of standardized responses for statistical modeling and hypothesis testing. A structured questionnaire survey was developed based on established constructs from prior studies on AI readiness [2], technostress [5], human–AI collaboration [7], and ethical governance [11]. The survey items were measured on a five-point Likert scale ranging from "strongly disagree (1)" to "strongly agree (5)."

4.2 Population and Sampling

The target population comprised employees and middle-level managers working in AI-adopting SMEs across the manufacturing, service, and IT sectors. SMEs were selected according to the definitions of the Ministry of Micro, Small and Medium Enterprises (MSME), India—organizations with fewer than 250 employees and turnover below ₹250 crore. A stratified random sampling technique was applied to ensure sectoral representation. Invitations were sent to 450 employees across 60 SMEs, out of which 312 valid responses were received (response rate: 69.3%). This sample size exceeds the recommended minimum of 200 for structural equation modeling (SEM), ensuring adequate statistical power [3], [8].

4.3 Data Collection Procedure

Data were collected through a combination of online surveys and in-person distribution. Respondents were briefed about the study objectives and assured of data confidentiality. Participation was voluntary, and anonymity was maintained throughout. The questionnaire included the following sections:

- Section A: Demographic and organizational data (age, gender, role, industry type, firm size).
- Section B: Extent and type of AI tools adopted (automation systems, decision support, predictive analytics).
- Section C: Perceptions related to mediating factors—organizational culture, autonomy, technostress, and ethics.
- Section D: Self-reported measures of employee productivity and job satisfaction.

All items were pre-tested with ten experts from academia and industry to ensure clarity and contextual relevance. The pilot test (n = 30) yielded a Cronbach's alpha of 0.86, indicating high internal reliability.

4.4 Measurement of Constructs

The measurement scales for each construct were adapted and validated from previous research:

Table 1. Measurement scales for each construct

Construct	Source	Example Item	Reliability (α)
AI Adoption	[2], [3]	"Our organization uses AI-based systems for process optimization."	0.88
Organizational Culture & Leadership	[1], [7]	"Management encourages experimentation with new AI tools."	0.85
Employee Autonomy & Skill Development	[3], [8], [10]	"I can make decisions independently when using AI systems."	0.82
Technostress Management	[5], [6]	"AI tools increase my workload pressure." *(reverse-coded)*	0.84
Ethical & Governance Practices	[11]	"Our organization ensures fair and transparent use of AI decisions."	0.86
Employee Productivity	[4], [9]	"AI technologies have improved my work output and efficiency."	0.90

Each construct was modeled as a latent variable measured by three to five observed indicators. Confirmatory factor analysis (CFA) was used to assess construct validity and convergent reliability.

4.5 Data Analysis Techniques

Data analysis was performed using SPSS 28 and AMOS 26 software. The following steps were undertaken:

1. Descriptive Statistics: To summarize demographic profiles and initial perceptions of AI adoption.
2. Reliability and Validity Tests: Cronbach's alpha and composite reliability were assessed for internal consistency; Average Variance Extracted (AVE) values above 0.5 confirmed convergent validity.
3. Correlation Analysis: Pearson's correlation coefficients measured the strength and direction of relationships between constructs.
4. Structural Equation Modeling (SEM): SEM tested the hypothesized relationships in the conceptual framework (Fig. 1), including direct and mediating effects of organizational and behavioral factors.
5. Mediation Analysis: The bootstrapping method (5,000 resamples) was employed to test indirect effects with 95% confidence intervals.
6. Model Fit Indices: Acceptable fit thresholds were: $\chi^2/df < 3.0$, CFI > 0.90, TLI > 0.90, RMSEA < 0.08 [9].

4.6 Ethical Considerations

The study adhered to standard research ethics protocols, including informed consent, confidentiality, and voluntary participation. No personal identifiers were collected. Ethical clearance was obtained from the affiliated academic institution prior to data collection. The methodological design ensures both quantitative rigor and contextual relevance in analyzing AI-driven productivity outcomes in SMEs. The next section (Section 5) presents empirical results and hypothesis testing, highlighting direct, mediating, and feedback relationships as conceptualized in Fig. 1.

5 Results and Discussion

5.1 Descriptive Statistics

Table 2 presents the demographic and organizational characteristics of the respondents. Among the 312 valid participants, 58% were male and 42% female. Nearly half (47%) were employed in manufacturing, 32% in information technology, and 21% in services. A majority (63%) held mid-level managerial or technical roles, and 71% had more than three years of experience using digital or AI-assisted tools. These demographics indicate adequate exposure to AI technologies within SME operations.

Table 2. Respondent Profile

Variable	Category
Gender	Male (58), Female (42)
Industry Type	Manufacturing (47), IT (32), Services (21)
Role	Managerial (38), Technical (25), Operational (37)
AI Experience	< 1 year (12), 1–3 years (17), > 3 years (71)

5.2 Reliability and Validity Assessment

All constructs exceeded the Cronbach's alpha threshold of 0.7, confirming strong internal reliability (range: 0.82–0.90). The Composite Reliability (CR) values ranged from 0.84 to 0.91, while the Average Variance Extracted (AVE) values exceeded 0.5, indicating convergent validity. Discriminant validity was confirmed as the square root of each AVE exceeded inter-construct correlations. These results align with best-practice guidelines for structural modeling [9].

5.3 Structural Model and Fit Indices

The hypothesized structural model (Fig. 1) was tested using Structural Equation Modeling (SEM). The results indicated a strong model fit:

Table 3. Model Fit Indices

Fit Index	Recommended Value	Obtained Value
χ^2/df	< 3.0	2.31
CFI	> 0.90	0.943
TLI	> 0.90	0.936
RMSEA	< 0.08	0.051

The model demonstrates good fit, validating the conceptual framework's predictive capability for AI adoption and productivity relationships.

5.4 Hypothesis Testing

The hypotheses were tested for both direct and mediating relationships using SEM path coefficients.

Table 4. Hypothesis Testing Results

Hypothesis	Relationship	Standardized β	p-value	Result
H1	AI Adoption → Employee Productivity	0.41	< 0.001	Supported
H2	AI Adoption → Organizational Culture & Leadership	0.56	< 0.001	Supported
H3	AI Adoption → Employee Autonomy & Skill Development	0.48	< 0.001	Supported
H4	AI Adoption → Technostress Management	–0.27	< 0.01	Supported (negative effect)
H5	AI Adoption → Ethical & Governance Practices	0.52	< 0.001	Supported
H6	Mediating Variables → Employee Productivity	0.59	< 0.001	Supported

The results show that AI Adoption has both direct and indirect effects on employee productivity. The mediating variables collectively explain 64% of the variance in productivity ($R^2 = 0.64$), confirming their central role in shaping AI outcomes.

5.5 Mediating Effects

Mediation analysis using the bootstrapping method (5,000 samples) revealed that three mediators had significant indirect effects:

1. Organizational Culture and leadership: $\beta = 0.23$, 95% CI [0.14, 0.34]; $p < 0.001$.
   – AI adoption fosters adaptive and innovation-friendly cultures that boost morale and collaboration [1], [7].
2. Employee Autonomy and Skill Development: $\beta = 0.19$, 95% CI [0.10, 0.29]; $p < 0.001$.
   – Skill empowerment enhances perceived control and efficiency in AI-aided tasks [3], [8], [10].
3. Ethical and Governance Practices: $\beta = 0.15$, 95% CI [0.07, 0.23]; $p < 0.01$.
   – Transparent policies increase trust, reducing anxiety toward automation [11].

Technostress Management had a partial mediation effect ($\beta = –0.08$, $p < 0.05$), indicating that poor digital ergonomics and lack of support can weaken AI's positive impact.

5.6 Discussion

The findings reinforce the notion that AI adoption enhances employee productivity primarily through organizational and human-centric mediators. The direct effect ($\beta = 0.41$) supports prior evidence that AI technologies improve decision accuracy and process efficiency [2], [3], [4]. However, the mediating strength ($\beta = 0.59$) underscores the importance of complementary managerial and cultural mechanisms.

Organizational Culture and Leadership

A culture that encourages experimentation and continuous learning enhances the success of AI initiatives [1], [7]. Transformational leadership behaviors—such as inspiring innovation and involving employees in AI decision-making—are critical to sustaining motivation and productivity.

Employee Autonomy and Skill Development

Consistent with Chen *et al.* [3] and Thomas and Cruz [10], employees who are empowered to use AI tools creatively exhibit higher output quality. Autonomy also mediates the psychological acceptance of AI, reducing fears of obsolescence and enhancing adaptability.

Technostress and Ethical Concerns

Richter and Unger [5] caution that uncontrolled automation may induce stress and job fatigue. The negative coefficient observed ($\beta = –0.27$) confirms that unmanaged technostress can partially offset productivity gains. Similarly, ethical and governance factors [11]—such as fairness in AI recommendations and privacy assurance—emerged as crucial determinants of sustained productivity.

Feedback Mechanism

Empirical data also support the feedback assumption in the conceptual model (Fig. 1). SMEs reporting high productivity levels were more likely to reinvest in AI tools, employee training, and ethical data policies, thus strengthening organizational readiness for subsequent digital transformations [8], [9], [10].

5.7 Theoretical and Managerial Implications

Theoretical Implications

This study contributes to the evolving literature by empirically validating a mediating framework linking AI adoption to employee productivity. The results extend socio-technical and human–AI collaboration theories [6], [7], [8] by confirming that balanced interaction between technology and human agency leads to optimal outcomes.

Managerial Implications

For SME managers, the results emphasize that productivity improvements depend not merely on technology investment but on fostering trust, ethical oversight, and learning-oriented leadership. Policies should prioritize:

- Ongoing AI literacy and training programs.
- Transparent AI decision logic communication.
- Flexible, autonomy-supportive work structures.
- Mechanisms to monitor and mitigate technostress.

The study provides empirical confirmation that AI adoption significantly improves employee productivity in SMEs, provided that adoption is accompanied by strong leadership, ethical governance, and employee empowerment. The next section (Section 6) concludes the study and provides actionable recommendations and future research directions.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Artificial Intelligence (AI) has emerged as a powerful catalyst for organizational transformation, enabling SMEs to enhance productivity, innovation, and competitiveness. This study investigated the impact of AI adoption on employee productivity (EP) within small and medium-sized enterprises, focusing on the mediating roles of organizational culture and leadership, employee autonomy and skill development, technostress management, and ethical governance. The empirical analysis confirmed that AI adoption has both direct and indirect effects on productivity. While the direct impact ($\beta = 0.41$) demonstrates that AI integration optimizes workflows and improves task efficiency, the indirect effects ($\beta = 0.59$) highlight the indispensable role of human-centric mediators. A supportive culture, participative leadership, and transparent governance practices significantly amplify AI's productivity benefits. Conversely, unmanaged automation and technostress partially weaken these positive effects. The study reaffirms that AI adoption alone does not guarantee performance improvement. Productivity gains materialize only when AI is embedded within an organizational environment that fosters learning, ethical accountability, and empowerment. These findings contribute to socio-technical systems and human–AI collaboration theory by establishing that the optimal outcomes emerge from balanced interaction between technology and human agency [6]–[8].

6.2 Managerial Recommendations

Based on the findings, the following practical recommendations are proposed for SME managers, leaders, and policymakers seeking to maximize the productivity benefits of AI integration:

1. Develop Human-Centric AI Strategies: AI implementation should be designed to augment human decision-making, not replace it. Managers should clearly communicate how AI supports employees' goals to mitigate anxiety and resistance [7], [8].
2. Promote Transformational Leadership and Learning Culture: Encouraging experimentation and continuous improvement fosters employee confidence in AI systems. Leadership should reward innovation and promote collective learning through cross-functional collaboration [1], [10].
3. Enhance Digital Literacy and Reskilling: Continuous AI literacy programs must be institutionalized to improve workforce adaptability. Employees with digital skills are better able to use AI tools effectively [3], [9].
4. Implement Ethical and Transparent Governance: Ethical AI deployment, data privacy assurance, and explainable AI models build trust and engagement. Governance policies should define data-use boundaries and ensure fairness in automated decision-making processes [11].
5. Monitor and Manage Technostress: Regular employee feedback mechanisms should be established to assess workload balance and stress levels. Flexible scheduling and human oversight in automation can prevent burnout [5], [6].
6. Foster Feedback-Based Reinforcement: Productivity metrics derived from AI systems should inform future adoption cycles. This feedback loop encourages iterative learning and ensures continuous performance improvement [8], [9], [10].

6.3 Policy Implications

From a policy perspective, the results highlight the need for inclusive digital transformation frameworks that extend AI access, literacy, and infrastructure to SMEs. Governments and industry associations should:

- Provide incentives for ethical and responsible AI deployment.
- Support sector-specific AI adoption toolkits and open data platforms.
- Facilitate public–private partnerships for SME workforce training.

Such initiatives would democratize AI adoption and prevent productivity inequality between digitally mature and nascent enterprises.

6.4 Limitations and Future Research Directions

Although the study offers valuable insights, several limitations open avenues for future research:

1. Cross-sectional Design: The data were collected at a single point in time; future longitudinal studies could capture evolving productivity patterns over extended AI adoption phases.
2. Self-Reported Productivity: Future work should integrate objective productivity metrics (e.g., task completion rates, performance analytics) alongside perceptual data to improve accuracy.
3. Sectoral and Regional Variations: Comparative studies across industries or countries can explore how institutional support and technological maturity shape AI-productivity dynamics.
4. Integration of Hybrid Human–AI Work Models: Further research should examine optimal task division between humans and AI, developing frameworks for shared cognition and adaptive collaboration [7], [8].
5. Inclusion of Emerging AI Technologies: Future analyses may include generative AI, adaptive learning models, and multimodal systems to assess how these next-generation tools impact creativity and knowledge work.

6.5 Final Remarks

This study establishes that AI adoption in SMEs enhances employee productivity only when implemented ethically, transparently, and with adequate human empowerment. The proposed model demonstrates that organizational culture, leadership, and employee capability development act as the primary conduits through which AI translates into measurable performance outcomes. For SMEs aspiring to thrive in the digital economy, the key lies not merely in adopting AI—but in adopting it responsibly, collaboratively, and humanely.

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Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

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