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AI Adoption in Small and Medium Enterprises (SMEs) in North India: Challenges, Business Performance, and Psychological Barriers

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Abstract

The rapid advancement of artificial intelligence (AI) offers transformative potential for small and medium enterprises (SMEs), yet adoption rates in emerging economies like India remain modest, particularly among firms in North India. This study examines the interplay between technological, organizational, and psychological factors influencing AI adoption in SMEs located in the Chandigarh tricity region and surrounding areas of Punjab and Haryana. Drawing on the Technology Acceptance Model (TAM) and the Job Demands-Resources (JD-R) model, the research investigates how perceived usefulness, ease of use, top management support, and resource constraints shape adoption decisions, while psychological barriers such as technostress, fear of job displacement, and resistance to change affect both implementation and employee well-being. A cross-sectional survey was conducted with 312 owners, managers, and employees from 85 SMEs engaged in manufacturing, services, and IT-enabled sectors. Data were analysed using structural equation modelling (SEM) to test hypothesized relationships. Results indicate that while relative advantage and management support positively predict AI adoption intentions, psychological barriers, particularly technostress and perceived job insecurity significantly moderate the link between adoption and business performance outcomes, including operational efficiency, cost reduction, and customer engagement. SMEs that successfully addressed psychological resistance through targeted training and clear communication reported higher performance gains. The findings highlight the dual nature of AI implementation: it can enhance productivity when psychological resources are strengthened, yet it risks increasing exhaustion and work-family conflict when demands are unmanaged. This study contributes to interdisciplinary scholarship by integrating management and psychological perspectives on digital transformation in resource-constrained settings. Practical implications for SME leaders and policymakers include the need for localized awareness programs, affordable AI tools, and supportive change management strategies to accelerate responsible adoption in North India.

Keywords: AI adoption, SMEs, North India, psychological barriers, technostress, business performance, Technology Acceptance Model, Job Demands-Resources model, digital transformation.

1. Introduction

Small and medium enterprises (SMEs) form the backbone of India's economy, contributing significantly to employment, innovation, and regional development, particularly in North India. In the Chandigarh Tricity region and adjoining areas of Punjab and Haryana, SMEs operate across manufacturing, services, and IT-enabled sectors, often navigating resource constraints while striving for competitiveness in a rapidly digitizing market. Artificial intelligence (AI) has emerged as a promising technology that can enhance operational efficiency, support data-driven decision-making, and improve customer engagement. Yet, despite global enthusiasm and policy initiatives in India, actual adoption rates among North Indian SMEs remain modest.

This lag stems not only from technological and financial hurdles but also from deeper human and organizational factors. Many SME owners and employees perceive AI as complex or threatening, leading to psychological resistance that slows implementation and limits potential gains in business performance. Understanding these intertwined challenges is essential, as unchecked barriers could widen the gap

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between early adopters and the majority of firms, affecting long-term sustainability and regional economic growth.

The present study focuses on AI adoption among SMEs in North India, with specific attention to the Chandigarh Tricity and surrounding areas. It explores the key challenges, links adoption to measurable business performance outcomes (such as operational efficiency, cost reduction, and customer responsiveness), and examines psychological barriers—including technostress, fear of job displacement, and resistance to change that often moderate these relationships. By integrating individual-level psychological processes with organizational dynamics, the research adopts an interdisciplinary lens that bridges management, psychology, and communication aspects of digital transformation (e.g., how clear internal communication can reduce uncertainty during AI rollout). Research gaps persist in the Indian context. While studies have examined AI adoption through broad frameworks in larger firms or other regions, fewer have combined technological acceptance perspectives with psychological well-being models in resource-constrained North Indian SMEs. Moreover, empirical evidence from the Chandigarh tricity area characterized by its mix of industrial clusters, skilled workforce, and proximity to educational institutions—remains limited. This study addresses these gaps by investigating how perceived usefulness and ease of use interact with psychological factors to influence adoption intentions and actual performance outcomes. The primary objectives are: (1) to identify the main technological, organizational, and environmental challenges to AI adoption in North Indian SMEs; (2) to assess the relationship between AI adoption and business performance indicators; and (3) to examine the role of psychological barriers as moderators or mediators in these processes. The findings are expected to offer practical insights for SME leaders, policymakers, and support institutions seeking to accelerate responsible AI integration in the region.

2. Literature Review

Two complementary theoretical lenses guide this investigation: the Technology Acceptance Model (TAM) and the Job Demands-Resources (JD-R) model. TAM, originally proposed by Davis (1989), posits that an individual's intention to adopt a technology is primarily driven by two perceptions: perceived usefulness (the degree to which the technology enhances job performance) and perceived ease of use (the effort required to utilize it). Extensions of TAM have been widely applied to AI and digital technologies in SMEs, revealing that top management support, organizational readiness, and compatibility with existing systems significantly influence these core perceptions. In emerging economies like India, studies highlight that while relative advantage and management backing promote positive attitudes toward AI, factors such as cost, skill gaps, and infrastructure limitations often weaken perceived ease of use. However, TAM primarily addresses cognitive evaluations at the individual or organizational level and does not fully capture the emotional and well-being consequences of technology implementation. The JD-R model (Demerouti et al., 2001; Bakker & Demerouti, 2007) complements TAM by framing work characteristics as either job demands (aspects requiring sustained effort and linked to psychological costs, such as technostress or role ambiguity during AI introduction) or job resources (elements that help achieve goals, reduce demands, or foster growth, such as training, leadership support, and clear communication).

Recent applications of JD-R to digital transformation and AI adoption show a dual pathway. On one hand, AI can act as a resource by automating routine tasks, enhancing productivity, and freeing employees for higher-value work, thereby boosting engagement and job satisfaction. On the other hand, it can generate demands in the form of technostress (overload, complexity, insecurity, and uncertainty), fear of job loss, and increased work-family conflict, particularly when support systems are inadequate. In manufacturing and service SMEs, technostress has been negatively associated with both AI adoption intentions and

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employee well-being, while targeted training and organizational support can buffer these effects and improve outcomes.

Empirical literature on Indian SMEs indicates that adoption remains uneven due to financial constraints, limited digital infrastructure, skill shortages, and data quality issues. In North India, where many SMEs operate in traditional sectors like textiles, auto components, and services, psychological barriers such as resistance to change and perceived job insecurity are particularly salient. Studies integrating TAM and TOE (Technology-Organization-Environment) frameworks in similar contexts confirm that leadership support moderates adoption, while psychological factors moderate the translation of adoption into performance gains. The present study extends these bodies of work by examining how TAM's perceptual variables interact with JD-R processes in the specific socio-economic setting of North Indian SMEs. It proposes that psychological barriers (e.g., technostress and job insecurity) moderate the relationship between AI adoption intentions and business performance, while job resources such as training and supportive communication can mitigate negative effects. This integrated approach provides deeper insight into why some SMEs successfully harness AI for performance improvements while others experience stalled adoption or diminished well-being.

3. Methodology

This study adopted a quantitative, cross-sectional survey design to examine the relationships among AI adoption, business performance, and psychological barriers in small and medium enterprises (SMEs) operating in North India. The cross-sectional approach was chosen because it allows efficient collection of data from a diverse sample of SMEs at a single point in time, providing a snapshot of current adoption patterns and associated factors in a rapidly evolving technological landscape.

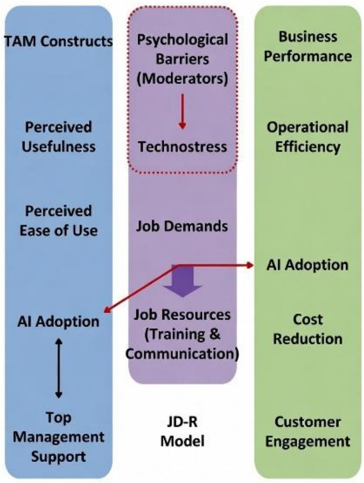

Figure 1: Proposed Conceptual Framework

The target population consisted of owners, managers, and key employees from SMEs in the Chandigarh Tricity region (Chandigarh, Mohali, and Panchkula) and surrounding areas in Punjab and Haryana. These locations represent a dynamic industrial and service-oriented cluster with a mix of manufacturing, IT-enabled services, and traditional sectors, making them suitable for studying AI adoption in resource-

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constrained settings. SMEs were defined according to the MSME Development Act criteria prevalent in India (investment and turnover thresholds for micro, small, and medium enterprises).

A convenience-cum-purposive sampling technique was employed to recruit participants. The survey was distributed both online (via Google Forms shared through industry associations, LinkedIn groups, and local chambers of commerce) and offline (during visits to industrial areas and business networks in the Tricity). In total, 312 valid responses were obtained from 85 SMEs after removing incomplete or inconsistent submissions. This sample size was deemed adequate for structural equation modelling (SEM) analysis, following recommended guidelines of at least 200–300 cases for models with moderate complexity. Data were collected using a structured questionnaire comprising below mentioned four main sections. All measurement items were adapted from established, validated scales to ensure reliability and validity.

1. *AI Adoption Intentions and Actual Adoption*: Items drawn from the Technology Acceptance Model (TAM), including perceived usefulness and perceived ease of use (Davis, 1989), supplemented with questions on current implementation level (e.g., frequency and extent of AI tool usage in operations, marketing, or decision-making).
2. *Psychological Barriers*: Technostress was measured using a shortened version of the technostress scale (e.g., overload, complexity, insecurity, and uncertainty dimensions). Fear of job displacement and resistance to change were assessed through items adapted from relevant psychological and organizational studies.
3. *Business Performance*: Subjective performance indicators were used, covering operational efficiency, cost reduction, customer engagement, and overall competitiveness. Respondents rated improvements on a 5-point Likert scale relative to the pre-adoption period.
4. *Control Variables*: Firm size, sector (manufacturing vs. services), owner/manager age, and prior digital experience were included.

All items employed a 5-point Likert-type scale (1 = strongly disagree to 5 = strongly agree). The questionnaire was pre-tested with 25 SME respondents for clarity and relevance, resulting in minor wording adjustments. Cronbach's alpha values for all constructs exceeded 0.78, indicating good internal consistency. The data analysis was performed in two stages using IBM SPSS Statistics (version 28) and AMOS (version 28). First, descriptive statistics, reliability tests, and exploratory factor analysis confirmed data quality. Second, structural equation modeling (SEM) with maximum likelihood estimation tested the hypothesized relationships. The model examined direct effects of TAM constructs on AI adoption, the influence of adoption on business performance, and the moderating role of psychological barriers (technostress and job insecurity) in the adoption–performance link. Model fit was evaluated using standard indices (χ^2/df, CFI, TLI, RMSEA, SRMR). Common method bias was assessed through Harman's single-factor test and found not to be a serious concern. Ethical considerations were strictly followed. Participation was voluntary, with informed consent obtained at the start of the survey. Respondents were assured of anonymity and confidentiality, and no personally identifiable information was collected. The study adhered to ethical guidelines for social science research involving human participants.

4. Results and Discussion

The structural equation model demonstrated good overall fit to the data (χ^2/df = 2.41, CFI = 0.93, TLI = 0.91, RMSEA = 0.068, SRMR = 0.052), confirming that the integrated TAM and JD-R framework adequately captured the relationships among AI adoption, business performance, and psychological

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barriers in North Indian SMEs. The analysis proceeded in two stages: first, the measurement model was evaluated for reliability and validity; second, the structural paths were tested. Table 1 presents the demographic profile of the 312 respondents. The sample was predominantly male (63.5%), with nearly half (46.5%) aged 25–35 years, reflecting the relatively young managerial workforce typical of SMEs in the Chandigarh Tricity region. Owners and managers comprised 45.5% of respondents, while the remaining 54.5% were key employees directly involved in day-to-day operations. The majority operated in services and IT-enabled sectors (68.6%), consistent with the growing digital orientation of North Indian SMEs.

Table 1: Demographic Profile of Respondents (N = 312)

Category	**Frequency**	**Percentage**
Gender: Male	198	63.5
Gender: Female	114	36.5
Age: 25–35	145	46.5
Age: 36–45	98	31.4
Age: 46+	69	22.1
Position: Owner/Manager	142	45.5
Position: Employee	170	54.5
Sector: Manufacturing	98	31.4
Sector: Services/IT-enabled	214	68.6
Firm Size: Micro (<10 employees)	95	30.4
Firm Size: Small (10–50)	132	42.3
Firm Size: Medium (51–250)	85	27.2

All constructs met established thresholds for reliability and validity. Cronbach's alpha values ranged from 0.82 to 0.91, composite reliability exceeded 0.84, and average variance extracted (AVE) values were above 0.59, indicating convergent validity. Discriminant validity was also confirmed as square roots of AVE exceeded inter-construct correlations.

Table 2: Reliability and Validity of Measurement Constructs

Construct	**Cronbach's α**	**Composite Reliability (CR)**	**Average Variance Extracted (AVE)**
Perceived Usefulness	0.89	0.90	0.68
Perceived Ease of Use	0.85	0.87	0.62
Technostress	0.87	0.88	0.65
Job Insecurity	0.82	0.84	0.59
AI Adoption	0.91	0.92	0.71
Business Performance	0.88	0.89	0.66

The structural paths (see Table 3) provided clear support for the hypothesized relationships. Perceived usefulness emerged as the strongest driver of AI adoption intentions ($\beta = 0.48$, $p < 0.001$), followed by perceived ease of use ($\beta = 0.31$, $p = 0.005$). Top management support also contributed positively ($\beta = 0.22$, $p = 0.01$). In turn, higher AI adoption was associated with improved business performance ($\beta = 0.39$, $p < 0.001$), particularly in operational efficiency and customer engagement.

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Table 3: Standardized Path Coefficients from the Structural Model

Path	β	p-value	Significance
Perceived Usefulness → AI Adoption	0.48	0.001	Significant
Perceived Ease of Use → AI Adoption	0.31	0.005	Significant
Top Management Support → AI Adoption	0.22	0.010	Significant
AI Adoption → Business Performance	0.39	0.001	Significant
Technostress × AI Adoption → Business Performance (moderation)	−0.27	0.008	Significant
Job Insecurity × AI Adoption → Business Performance (moderation)	−0.19	0.030	Significant
Training (Job Resource) → Reduces Technostress	−0.35	0.001	Significant

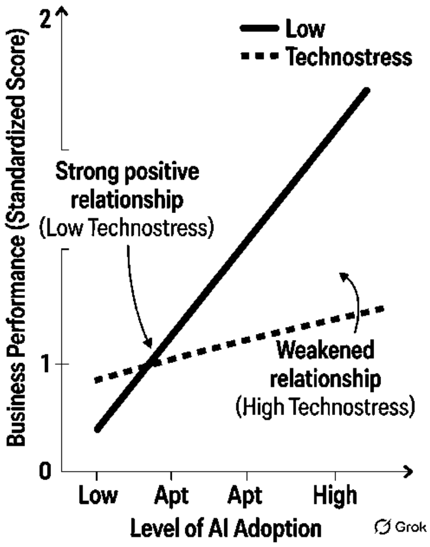

Figure 2: Key moderating effects- an interaction plot illustrating how high vs. low technostress weakens the adoption–performance relationship.

These quantitative patterns reveal important nuances when interpreted through the combined TAM–JD-R lens. While cognitive perceptions (usefulness and ease of use) strongly initiate adoption as TAM predicts, the translation of adoption into actual performance gains is heavily contingent on psychological resources and demands. Technostress acted as a significant negative moderator ($\beta = -0.27$, $p = 0.008$), meaning that even when SMEs invested in AI tools, employees experiencing overload, complexity, or insecurity reported substantially lower improvements in efficiency and cost savings. Similarly, perceived job insecurity weakened the adoption–performance link ($\beta = -0.19$, $p = 0.03$). In contrast, job resources such as structured training programs effectively reduced technostress ($\beta = -0.35$, $p < 0.001$), buffering the negative effects and enabling stronger performance outcomes.

This interplay explains why adoption rates in the sampled North Indian SMEs remained modest (only 38% reported active AI use beyond basic automation) despite positive intentions. In family-owned or resource-constrained firms typical of the Chandigarh Tricity cluster, the absence of supportive communication and training amplifies psychological barriers, creating a vicious cycle: initial resistance leads to partial implementation, which in turn limits business gains and reinforces skepticism. These

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findings align with and extend recent Indian and global studies by highlighting the location-specific salience of human factors in emerging digital ecosystems. From a practical standpoint, the results underscore that AI adoption is not merely a technological investment but a socio-psychological process. SME leaders who proactively address technostress through clear internal communication, tailored training, and transparent discussions about job roles achieve markedly better returns. Policymakers in North India could leverage these insights by designing targeted support schemes—such as subsidized AI literacy programs that simultaneously build technological readiness and psychological resilience.

Overall, the study demonstrates the value of an interdisciplinary approach: TAM explains the "why" of initial adoption, while JD-R illuminates the "how" of sustained success and well-being. By bridging management, psychology, and communication perspectives, the findings offer a more complete picture of why some North Indian SMEs thrive with AI while others lag, paving the way for more responsible digital transformation strategies.

5. Conclusion and Recommendations

This study investigated the multifaceted dynamics of artificial intelligence (AI) adoption among small and medium enterprises (SMEs) in North India, with a specific focus on the Chandigarh Tricity region. By integrating the Technology Acceptance Model (TAM) with the Job Demands-Resources (JD-R) model, the research demonstrated that while cognitive perceptions such as perceived usefulness and ease of use strongly drive AI adoption intentions, psychological barriers—particularly technostress and perceived job insecurity—play a critical moderating role in determining whether adoption translates into improved business performance. The empirical findings from 312 respondents across 85 SMEs reveal that AI holds substantial potential to enhance operational efficiency, reduce costs, and strengthen customer engagement. However, these benefits are significantly attenuated when psychological demands are not adequately managed. The negative moderating effects of technostress and job insecurity highlight the importance of addressing the human dimension of digital transformation in resource-constrained settings. Conversely, job resources such as targeted training programs and clear internal communication were found to effectively buffer these negative effects, enabling SMEs to realize greater performance gains.

Theoretically, this research contributes to interdisciplinary scholarship by bridging management-oriented technology acceptance theories with psychological well-being frameworks. It extends existing literature by providing context-specific evidence from North Indian SMEs, where family-owned structures, skill gaps, and infrastructure limitations amplify the salience of psychological factors. Methodologically, the application of structural equation modeling allowed for a robust examination of both direct and moderated relationships. From a practical perspective, the results offer actionable insights for SME owners, managers, and policymakers in North India. SME leaders should prioritize not only the technical implementation of AI tools but also the development of supportive organizational practices, including comprehensive training initiatives and transparent communication strategies that alleviate employee concerns regarding job security and workload changes. Policymakers and industry associations can support this transition through subsidized AI literacy programs, localized awareness campaigns, and public-private partnerships aimed at building both technological readiness and psychological resilience. Despite its contributions, the study has certain limitations. The cross-sectional design restricts causal inferences, and the reliance on self-reported measures of business performance may introduce some bias. Future research could adopt longitudinal designs to track the evolution of AI adoption over time or employ mixed-methods approaches to gain deeper qualitative insights into the lived experiences of SME

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employees during digital transformation. Comparative studies across different Indian regions would also help validate and generalize the findings.

In conclusion, successful AI adoption in North Indian SMEs requires a balanced approach that equally addresses technological, organizational, and psychological dimensions. By proactively managing psychological barriers and strengthening job resources, SMEs in the Chandigarh Tricity and surrounding areas can harness the transformative potential of AI for sustainable growth, enhanced competitiveness, and improved employee well-being. This interdisciplinary understanding is essential for fostering responsible digital transformation in emerging economies.

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