# Structural and Perceptual Constraints in AI Adoption: Financial and Human Capital Challenges Facing Small Businesses in the Era of Industry 4.0

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## Abstract

Our study investigates the structural complexities and perceptual constraints associated with the implementation of digitization and Artificial Intelligence (AI) in firms, with a specific focus on small and medium-sized enterprises (SMEs) operating in the context of Industry 4.0. It explores the impact of financial and human resource limitations, employee resistance, data privacy concerns, and the role of digital leadership in AI adoption. The research adopts a mixed-methods approach, incorporating a literature review and a structural equation modeling (SEM) analysis to examine the hypothesized relationships between perceived barriers and firms' adoption of AI. Key indicators such as RMSEA, CFI, and TLI were used to assess model fitness, while regression coefficients and p-values determined the strength and significance of the relationships.

The findings reveal that the perception of financial limitations does not significantly hinder AI adoption, challenging conventional assumptions. Conversely, a lack of qualified personnel shows a weak but notable negative correlation with AI implementation capacity. Resistance from employees, initially perceived as a barrier, was found to have a surprisingly positive effect—possibly due to prior exposure to automation. Ethical concerns and data privacy did not significantly deter AI initiatives, with firms adhering to GDPR frameworks. The lack of awareness regarding available funding opportunities emerged as a notable external constraint.

This study offers original insights into how internal perceptions and structural limitations shape the digital transformation journey of SMEs. It moves beyond deterministic views of financial barriers, highlighting the nuanced interplay between organizational readiness and human factors.

The results underscore the need for targeted skill development, transparent AI communication strategies, and improved access to funding information. Policymakers and firm leaders should prioritize digital leadership, workforce reskilling, and inclusive innovation to foster sustainable AI integration in SMEs.

## Keywords

Artificial Intelligence Adoption, Digital Transformation Challenges, Small and Medium Enterprises (SMEs), Financial and Human Capital Constraints, Employee Resistance to Automation, Ethical and Data Privacy Concerns

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## Introduction

The implementation of Artificial Intelligence (AI) in business operations has emerged as both a strategic opportunity and a complex organizational challenge. While AI offers the potential to enhance operational efficiency, decision-making, and competitive advantage, its adoption is often hindered by significant structural and perceptual barriers—particularly in small and medium-sized enterprises (SMEs). Recent research emphasizes that key obstacles include financial limitations, shortage of skilled personnel, and employee resistance, which are intensified in the context of Industry 4.0 (Soni et al., 2020; Barsha and Munshi, 2024; Morandini et al., 2023). Furthermore, ethical concerns and data privacy issues have become increasingly prominent, as firms grapple with the integration of AI within frameworks that ensure transparency and regulatory compliance (Chatterjee et al., 2020; von Eschenbach, 2021). Our paper investigates the specific interplay between perceived financial and human capital constraints and the firms' ability to adopt AI-driven solutions. In contrast to dominant narratives, the findings challenge the assumption that limited financial resources are a major deterrent, revealing instead that motivational and informational gaps may be more significant. The study also explores how a perceived lack of qualified personnel affects AI readiness and highlights the paradoxical role of employee resistance, which may, under certain conditions, facilitate rather than obstruct AI integration. To address these questions, the study employs a mixed-methods approach combining literature review with structural equation modeling (SEM) to test two key hypotheses related to financial and personnel-related constraints. The structure of the paper is as follows: after this introduction, Section 2 reviews the scientific literature; Section 3 presents the methodology; Section 4 discusses the findings; and Section 5 concludes with managerial implications and recommendations for future research.

## 1.Review of the scientific literature

The adoption of Artificial Intelligence (AI) presents notable challenges for small and traditional enterprises, with high financial investment remaining one of the most significant obstacles. The costs associated with research and development (RandD)—particularly those related to acquiring and processing high-quality datasets for training customized AI models—often exceed the financial capacities of such firms (Soni et al., 2020; Okeke et al., 2024). Despite AI's recognized potential to reduce human error, increase operational efficiency, and optimize resource allocation, many traditional businesses lack the necessary digital infrastructure to support these advancements (Apu, 2025). Furthermore, AI implementation typically demands parallel investment in complementary technologies such as sensors, robotics, systems integration, and cybersecurity frameworks (Barsha and Munshi, 2024). While AI-based tools like dynamic pricing algorithms may enable small and medium-sized enterprises (SMEs) to adapt rapidly to market changes (Barua et al., 2024), the overall cost of full-scale deployment remains a considerable deterrent (Rana et al., 2024).

A further constraint is the limited availability of skilled professionals in AI, which hampers organizational capacity to design, implement, and maintain intelligent systems (Barsha et al., 2024). Morandini et al. (2023) argue that closing this talent gap requires a strategic assessment of internal capabilities and the development of targeted training initiatives. However, to avoid such investments, many companies prefer to recruit pre-trained professionals, inadvertently deepening the industry-wide skills shortage. For SMEs in particular, the financial burden of establishing a comprehensive AI infrastructure can severely impact their ability to remain competitive in increasingly automated environments (Rane et al., 2024). This challenge is exacerbated by limited access to funding, especially for firms serving niche markets (Thadani, 2023). Nonetheless, the long-term benefits of AI remain substantial, with applications in predictive analytics, intelligent automation, and personalized services offering transformative potential for business models across sectors (Mutasa et al., 2024).

Irrespective of organizational size, sector, or resource availability, there is a growing institutional commitment toward enhancing cybersecurity and mitigating operational risks (Shetty, 2023; Cai et al., 2023). Within this framework, the C.I.A. triad—confidentiality, integrity, and availability—has emerged as a foundational model for safeguarding information systems and sensitive data assets (Nie, 2024). This heightened focus on data protection has, in turn, accelerated interest in the deployment of AI-driven cybersecurity solutions. The imperative is further amplified by widespread consumer hesitancy to disclose personal and sensitive data, particularly financial and medical information, due to persistent privacy concerns (Chatterjee et al., 2020; Bijlsma et al., 2023). When strategically integrated into enterprise platforms such as customer relationship management (CRM) systems, artificial intelligence holds considerable potential to reinforce trust through robust data security protocols.

Empirical insights from the pharmaceutical sector illustrate this development, demonstrating that AI integration correlates with improved adherence to data protection regulations and a marked reduction in data breach incidents (Syed, 2022). In addition to enhancing compliance, AI contributes to cybersecurity resilience by leveraging machine learning to identify and learn from prior attack vectors, while employing predictive analytics to anticipate and neutralize emerging threats in real time (de Azambuja et al., 2023). Beyond threat detection, AI facilitates the automation of incident response protocols and augments the capabilities of cybersecurity professionals by providing advanced diagnostic and analytical tools (Familoni, 2024).

Employee resistance to the implementation of Artificial Intelligence (AI) is largely driven by concerns regarding potential job displacement. According to Raisch et al. (2021) and Noordeen (2024), this fear is fueled by the widespread perception that AI is primarily designed to automate human tasks rather than to support or enhance employee roles within organizations.

One of the most commonly cited barriers in the academic literature regarding AI adoption is the technology's inability to replicate essential human interaction traits such as empathy (Alam, 2022), emotional intelligence, morality (Gerrans, 2024), and interpersonal relationships formed within teams (Booyse and Scheepers, 2024). Although emotion recognition technologies in AI often rely on analyzing facial expressions, speech patterns, and physiological cues, the accuracy and reliability of these systems can be compromised by cultural diversity and biases embedded in the training datasets (Singh et al., 2024). However, recent studies indicate a growing research focus on addressing these limitations. Neural networks are showing promise in recognizing emotional patterns, which can be integrated into more advanced AI systems to improve emotional intelligence, thereby fostering more natural and human-like interactions (Preetha, 2024; Wu, 2024; Siwek et al., 2024; Vanitha et al., 2024).

Addressing the multifaceted resistance to AI adoption necessitates a shift in its organizational positioning—from a substitute for human leadership to a complementary decision-support system. Empirical evidence suggests that employees exhibit lower acceptance of decisions generated by artificial systems, particularly when such systems are perceived as lacking alignment with organizational culture and social norms (Sumarlin and Kusumajaya, 2024). These perceptions can erode morale and reduce overall productivity. Resistance is further intensified by limited transparency in algorithmic processes, notably in task prioritization, as well as by disruptions to established workflows stemming from insufficient change management strategies (López-García and Rojas, 2024; Neumann et al., 2024).

Noordeen (2024) identifies a persistent tension between organizational economic imperatives and employees' anxieties regarding job displacement, which frequently manifests in avoidance behaviors. Mabungela (2023) corroborates this, noting that automation-related uncertainty is exacerbated when employee perspectives are excluded from the implementation discourse. Moreover, SimanTov-Nachlieli (2023) observes that high-performing employees may actively resist AI-driven tools, perceiving them as threats to personal agency and professional relevance. To overcome such resistance, scholars advocate for a comprehensive, ethically grounded change strategy. This includes transparent communication, inclusive decision-making, targeted employee training, and the establishment of resilient organizational structures. Noble and Chahal (2024) stress the importance of fostering a culture of inclusion anchored in leadership accountability and innovation openness. Meanwhile, Madanchian and Taherdoost (2025) emphasize that the success of AI integration is closely linked to digitally competent leadership, adaptive organizational culture, and the utilization of advances in natural language processing and machine learning. Ultimately, as Kanapathipillai et al. (2024) argue, bridging digital skill gaps, ensuring compliance with regulatory frameworks, and cultivating trust are indispensable for AI adoption. Singh and Pandey (2024) reinforce this position, underlining the pivotal role of strategic and visionary digital leadership in steering organizations through the intricate process of transitioning toward intelligent automation.

Booyse et al. (2024) emphasize several critical impediments to the integration of artificial intelligence (AI) in automated decision-making processes, chief among them being the erosion of user trust, limited transparency, and unresolved ethical dilemmas (Sethy et al., 2023). These issues largely stem from the inherent opacity of black-box AI models, which obscure the rationale behind algorithmic outputs and hinder interpretability for end-users. Additionally, such systems are susceptible to algorithmic bias and cybersecurity vulnerabilities, both of which further exacerbate trust deficits (Booyse and Scheepers, 2024; von Eschenbach, 2021). As a countermeasure, there is a growing shift towards white-box AI frameworks, which enhance transparency by elucidating the internal decision logic and enabling greater user oversight. However, the deployment of these systems necessitates continuous vigilance through real-time monitoring and the implementation of proactive strategies to detect and mitigate potential security breaches (Rana et al., 2022). Notably, the convergence of AI systems with business analytics tools introduces additional complexity, often resulting in a blurred interface that compromises the clarity and accountability of automated decision-making mechanisms. To mitigate such risks, the adoption of AI must be supported by clear data protection strategies and contingency plans for dealing with security incidents (Rana et al., 2022). At the same time, issues of data privacy and ethics have become a central topic in both academic and organisational discourse (Shukla and Taneja, 2024). The integration of AI into business operations brings with it numerous ethical challenges, including accountability in decision-making, fairness and data governance, which need to be addressed responsibly (Purwanto et al., 2024).

These concerns are no longer limited to academic circles, but are increasingly dominating the agendas of governments, media and the public as AI is used in more and more sectors (Shawky et al., 2023; Taneja et al., 2024; Pramanik, 2024). In particular, the adoption of AI in African higher education has highlighted specific risks in terms of institutional readiness and ethical compliance (Afolabi, 2024). Therefore, the responsible integration of AI requires a balanced and well-thought-out approach that considers both data security and the ethical dimensions of the technology.

Over recent years, funding opportunities for AI start-ups have increased significantly, driven by the perception that such investments yield high long-term returns (Soni et al., 2020). However, access to financing remains disproportionately limited for established firms across various business sectors. Compounding this issue is the insufficient dissemination of information regarding available funding programs, which further restricts firms' ability to secure capital for AI-related investments. As a result, established companies often rely solely on their internal financial resources to support strategic technology adoption. In contrast, early-stage ventures outside the fintech domain face considerable challenges in attracting AI-specific funding at the outset. Lee (2020) emphasizes that access to finance should be a central pillar of policy strategies related to the design, development, and deployment of AI, particularly within financial services. Addressing these financing disparities, Mhlanga (2021) advocates for the creation of robust public–private partnerships aimed at supporting both small-scale enterprises and mature firms in their efforts to invest in AI and machine learning technologies. Furthermore, financial institutions are encouraged to increase their commitment to AI investment, as a means of enhancing financial inclusion and fostering innovation in emerging industries (Mhlanga, 2021).

## 2.Research methodology

The SEM model computed the Chi-square values, the p-value, the Comparative Fit Index (CFI), the Tucker Lewis Index (TLI), the Root Mean Square Error Approximation (RMSEA), and the SEM beta regression estimates. The RMSEA, CFI, and TLI are goodness-of-fit indices. A good model–data fit is indicated by RMSEA < .06, CFI > .95, and TLI > .95 (Xia and Yang, 2019). The hypothesis tests are the Chi-square and p-values; p-value < 0.05 indicates a statistically significant relation between the variables in the regression model. The SEM beta regression coefficients indicate the direction and magnitude of the relation; negative values indicate an inverse relationship, while positive values indicate a directly proportional relationship (Keith, 2019). In cases where there is only 1 dependent variable and 1 independent variable, the SEM illustration figure is not presented.

**H1: The perception of a lack of financial resources correlates negatively with the perception of the adoption of AI for automation and the perception of data analysis.**

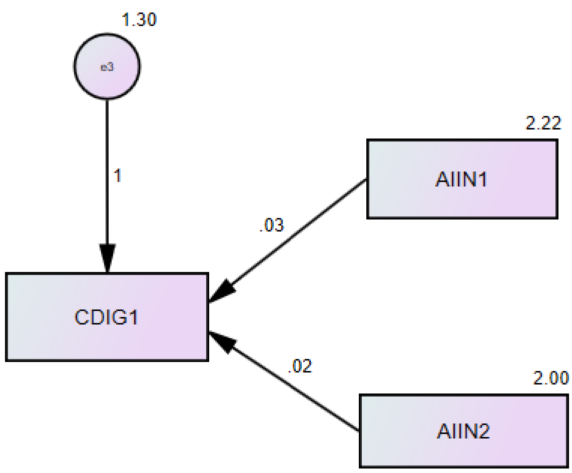


**Figure no.1. The H1 SEM regression graphical model**

**Table no. 1. Structural Equation Modeling (SEM) Results for H1 – Impact of Perceived Financial Constraints on AI Adoption for Automation and Data Analysis**

| | RMSEA | CFI | TLI | $\chi^2$ | p-value | $\beta$ |
|---|---|---|---|---|---|---|
| Model fitness | 1.005 | 0.003 | -2.034 | 137.251 | | |
| CDIG1 <--- AIIN1 | | | | | .643 | 0.030 |
| CDIG1 <--- AIIN2 | | | | | .792 | 0.018 |

The model data fit is poor. The lack of financial resources for digitization has a positive correlation with the perception of the adoption of AI for automation and data analysis. However, the p-values are higher than 0.05, indicating that the positive correlation is not significant and only happens by chance. The null hypothesis stating "The perception of a lack of financial resources correlates negatively with the perception of the adoption of AI for automation and the perception of data analysis" is rejected.

**H2: The perception of a lack of qualified personnel correlates negatively with the perception of the firm's ability to implement AI-driven initiatives.**

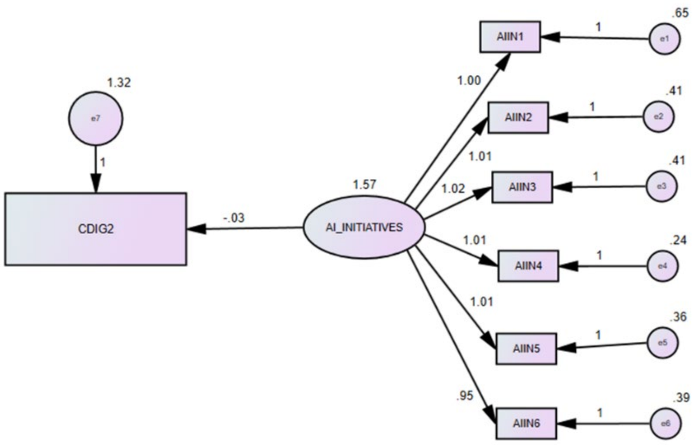


**Figure 2: The H2 SEM regression graphical model**

**Table no. 2. Structural Equation Modeling (SEM) Results for H2 – Impact of Perceived Lack of Qualified Personnel on Firms' Capacity to Implement AI-Driven Initiatives**

| | RMSEA | CFI | TLI | $\chi^2$ | p-value | $\beta$ |
|---|---|---|---|---|---|---|
| Model fitness | 0.124 | 0.968 | 0.951 | 42.892 | | |
| CDIG2 <--- AI_INITIATIVES | | | | | .739 | -0.027 |

The model data fit is good since CFI and TLI meet the threshold. The firm's AI initiatives (from AI IN 1-6) have a significant positive influence on the overall AI Initiatives since the regression estimates and the p-values are less than 0.05. The overall AI initiatives have a negative relationship with the lack of qualified personnel as a challenge in digitization, the relationship is not significant since the p-value is higher than 0.739. Since the lack of personnel correlates negatively with the perception of the firm's ability to implement AI-driven initiatives, the null hypothesis is accepted.

The study hypothesized that a lack of financial resources hindered the adoption of AI for automation and data analytics, however, this was rejected by the findings of the analysis. This implies that firms have the financial resources to invest in AI for automation and data analytics but have not made the effort. This can be investigated in a different study to understand the causes of the reluctance. Rather than the resistance of employees hindering the adoption of AI to increase automation efficiency, it had a positive impact. This could be explained by the employees already trained in some of the automation systems, and hence do not resist the technologies in use.

The introduction of new technology increases the automation efficiencies further. Likewise, the perception of ethical data privacy concerns did not hinder the adoption of AI initiatives in the firms; rather, firms follow the General Data Protection Regulations adopted by the EU, hence, the firms have no negativity about AI. The other hypotheses were accepted since they were in line with the literature review.

## 3.Results and discussion

The study hypothesized that a lack of financial resources hindered the adoption of AI for automation and data analytics, however, this was rejected by the findings of the analysis. This implies that firms have the financial resources to invest in AI for automation and data analytics but have not made the effort. This can be investigated in a different study to understand the causes of the reluctance. Rather than the resistance of employees hindering the adoption of AI to increase automation efficiency, it had a positive impact. This could be explained by the employees already trained in some of the automation systems, and hence do not resist the technologies in use. The introduction of new technology increases the automation efficiencies further. Likewise, the perception of ethical data privacy concerns did not hinder the adoption of AI initiatives in the firms; rather, firms follow the General Data Protection Regulations adopted by the EU, hence, the firms have no negativity about AI. The other hypotheses were accepted since they were in line with the literature review.

## Conclusions

The study highlights the multifaceted structural and perceptual challenges hindering the effective adoption of digitization and Artificial Intelligence (AI) in firms, particularly small and medium enterprises (SMEs) within the Industry 4.0 context. While AI promises enhanced efficiency, predictive capabilities, and competitive advantage, its widespread implementation remains obstructed by high financial costs, lack of digital infrastructure, and limited access to qualified personnel.

Contrary to expectations, the study's findings reveal that the perceived lack of financial resources does not significantly deter AI adoption, suggesting that firms may possess adequate capital but face motivational or strategic barriers. Additionally, resistance from employees—often presumed to stem from fears of job loss—was found to be less influential when training and transparency are present. Instead, a supportive organizational culture and inclusive leadership play a pivotal role in easing transitions toward automation.

The importance of data security and ethical AI usage also emerged as a major theme, with firms increasingly adopting AI-powered cybersecurity solutions and aligning with global data protection regulations. Ethical concerns and transparency in decision-making continue to influence trust in AI systems, underscoring the need for explainable, human-centered design. Furthermore, a widespread lack of awareness regarding funding opportunities—especially for non-startup firms—limits strategic investment in AI. The findings call for policy-level support, improved access to funding, investment in digital skills development, and a strong emphasis on organizational change management to enable effective digital transformation.

This study is limited by its focus on perceptual and structural barriers within a specific sample of SMEs, which may restrict the generalizability of findings across larger or more digitally mature organizations. Additionally, the reliance on self-reported data may introduce response bias. Future research should explore cross-sectoral comparisons and incorporate longitudinal designs to track the evolution of AI adoption over time. Investigating the psychological drivers behind managerial reluctance to embrace AI, despite financial capability, would also enrich the understanding of non-economic constraints. Broader, multinational studies could further validate the framework and inform targeted digital transformation policies.

Overall, the study underscores that AI adoption is not merely a technological issue but a complex interplay of financial, cultural, ethical, and strategic dimensions.

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