SRYAHWA PUBLICATIONS

Open Journal of Economics and Commerce
ISSN: 2638-549X | Volume 7, Issue 1, 2026
https://doi.org/10.22259/2638-549X.0701003

RESEARCH ARTICLE

AI-Powered Workflow Automation in Small Businesses

OMIGBODUN Olanrewaju Tolu[1], FAMILUSI Olayemi Babawole[2], AKINSOLA Samuel Akintunde[3], ADENIRAN Adedayo Ayomide[4], ADENIRAN Adetayo Olaniyi[5]

[1]*Department of Transport Planning and Logistics Studies, University of Ilesa, Ilesa, Nigeria.*
[2]*University of Ibadan.*
[3]*Sheffield Hallam University.*
[4]*Department of Geography and Planning, University of Ibadan, Nigeria.*
[5]*Centre for Transport and Logistics (CETRAL), University of Ilesa, Ilesa, Nigeria.*

Received: 02 March 2026 Accepted: 20 March 2026 Published: 23 March 2026

Corresponding Author: ADENIRAN Adetayo Olaniyi, Centre for Transport and Logistics University of Ilesa, Nigeria.

Abstract

Artificial Intelligence (AI)-driven workflow automation is transforming the operational landscape for small and medium-sized enterprises (SMEs), offering notable improvements in productivity, cost efficiency, and competitive edge. Yet, the adoption rate among SMEs remains inconsistent and relatively low, largely due to a range of internal limitations and external pressures. This research explores the level of AI adoption, the factors that influence it, the barriers faced, and its overall impact on SME performance. It draws on data from the 2023 Flash Eurobarometer 537 survey, which includes responses from more than 14,800 SMEs across 36 countries. Grounded in the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV), the study employs a mixed-methods design, combining descriptive analysis, logistic regression, and qualitative content analysis to deliver a comprehensive assessment. Findings reveal that AI adoption is significantly shaped by firm size, sector, turnover growth, and participation in innovation clusters, while barriers such as skill shortages, hiring difficulties, and digital infrastructure gaps remain prominent. This study contributes a contextual framework for responsible AI integration tailored to SME realities, offering practical recommendations for technology providers, SME leaders, and policymakers.

Keywords: Artificial Intelligence (AI), Adoption, SMES, Workflow Automation

1. Introduction

Workflow automation refers to the use of programmed instructions and automated feedback systems to manage and execute tasks efficiently and accurately, with the primary aim of streamlining operations, automate repetitive and mundane tasks, minimising human error, and increasing overall efficiency. This is often implemented through tools such as AI-driven Robotic Process Automation (RPA), which handles routine processes with little need for human input (Adeniran, Folorunso *et al.,* 2024; Al-Amin *et al*., 2024).

Artificial Intelligence (AI) has rapidly shifted from a futuristic concept to a transformative force in business process automation. In the last ten years, emerging technologies like AI, machine learning, and data analytics have significantly reshaped organizational performance across all areas of operation (Zhan *et al*., 2024). Today, AI stands out as a core strategic focus for firms across diverse industries, driving major changes in how businesses function (Ayinaddis, 2025; Brătucu *et al*., 2024). It is widely recognized as a key driver of future innovation, competitive advantage, and productivity gains (Zhan *et al*., 2024; McKinsey, 2020; Dwivedi *et al*., 2021b; Hradecky *et al*., 2022).

AI is increasingly being recognized as a General-Purpose Technology (GPT), distinguished by its ability to operate autonomously and continuously

Citation: OMIGBODUN Olanrewaju Tolu, FAMILUSI Olayemi Babawole, AKINSOLA Samuel Akintunde, *et al.* AI-Powered Workflow Automation in Small Businesses. Open Journal of Economics and Commerce. 2026;7(1): 13-45.

improve, with the potential to drive innovation and revive stagnant productivity across industries (Filippucci *et al*., 2024). The recent surge in AI-related investment and its expanding commercial use can be attributed to several factors, including the growing availability of diverse data sources, advancements in big data analytics, enhanced computational power, and declining technology costs (Zhan *et al*., 2024; Filippucci *et al*., 2024). Since around 2015, there has been a marked acceleration in the development of AI technologies such as machine learning, deep learning, and predictive analytics, alongside a sharp increase in academic and industry research in these areas (Ayinaddis, 2025; Mai *et al*., 2024; Babina *et al*., 2024).

Artificial Intelligence (AI) is commonly understood as a computer system capable of sensing, reasoning, and acting in ways that resemble human intelligence. These systems are designed to operate independently, make decisions, boost efficiency, and enhance productivity (Filippucci *et al*., 2024; Brynjolfsson, Li, and Raymond, 2023; Furman and Seamans, 2019; Ayinaddis, 2025; Arakpogun *et al*., 2021; Ghosh *et al*., 2018; Varma *et al*., 2024). Core AI technologies that support these capabilities include Natural Language Processing (NLP), Computer Vision, Machine Learning, and Predictive Analytics. When integrated with Robotic Process Automation (RPA), these tools help reduce manual workload, streamline operations, and drive productivity gains (Al-Amin *et al*., 2024; Tanti, 2025).

For small and medium-sized enterprises (SMEs), the importance of AI-powered workflow automation is particularly pronounced, as it helps address the inefficiencies and limited resources that often constrain their growth and performance (Adeniran *et al*., 2024; Al-Amin *et al*., 2024). SMEs are widely seen as central to economic development, especially in emerging and developing economies, where they play a vital role in job creation and innovation (Bala *et al*., 2024; Gherghina *et al*., 2020; Ayinaddis, 2025). In this context, adopting AI has become more than just a technological upgrade; it is now a strategic necessity for staying competitive in a fast-evolving and increasingly regulated digital economy (Sánchez *et al*., 2025).

Although AI holds clear benefits for businesses of all sizes, its adoption and impact vary notably between SMEs and larger, more established organizations (Ayinaddis, 2025; Abrokwah-Larbi &Awuku-Larbi, 2024; Czarnitzki *et al*., 2023). These differences are shaped by disparities in financial resources, technical expertise, cost structures, and access to institutional support (Ayinaddis, 2025). However, SMEs often enjoy certain advantages, such as greater flexibility, closer customer relationships, and leaner decision-making processes, which can help them adapt more quickly than their larger counterparts (Sánchez *et al*., 2025).

1.1 Specifically, AI solutions offer crucial advantages for SMEs, enabling them to

1. Boost Productivity and Efficiency: AI enables small businesses to streamline operations by taking over routine and repetitive tasks such as data entry, invoice processing, inventory control, and handling customer service queries. This shift allows employees to concentrate on higher-value, strategic, and creative functions, ultimately boosting productivity and overall performance (Al-Amin *et al*., 2024; Tanti, 2025; Amponsah *et al*., 2025; Blahušiaková, 2023; Nascimento & Meirelles, 2022; Sharma, 2023). For SMEs with limited financial resources, AI's ability to reduce operational costs while driving efficiency makes it a highly valuable tool (Amponsah *et al*., 2025; Jain *et al*., 2024; Sharma, 2023). Additionally, AI enhances decision-making and optimizes business processes, further supporting sustainable growth and competitiveness (Badghish & Soomro, 2024; Tanti, 2025).

2. Reduce Operational Costs: Streamlining processes, minimising human error, and optimising resource allocation through AI-powered systems (e.g., inventory management) directly contribute to significant cost savings and improved profitability (Al-Amin *et al*., 2024; Tanti, 2025; Amponsah *et al*., 2025; Badghish & Soomro, 2024).

3. Enhance Customer Experience and Engagement: AI-driven chatbots and virtual assistants enhance customer experience by delivering instant, personalized responses to queries, which helps boost satisfaction and build long-term loyalty (Al-Amin *et al*., 2024; Tanti, 2025; Amponsah *et al*., 2025). In addition, tools like recommendation engines and customized marketing efforts strengthen customer engagement and foster deeper relationships (Al-Amin *et al*., 2024).

4. Improve Decision-Making: AI-enabled dashboards and predictive analytics provide SMEs with real-time visibility into key performance indicators, enabling faster, data-informed decision-making (Adeniran *et al*., 2024). These tools help businesses anticipate market shifts, streamline supply chain operations, and respond proactively to emerging challenges (Al-Amin *et al*., 2024; Badghish & Soomro, 2024; Tanti, 2025). Machine learning, for instance, can make more accurate predictions and identify crucial patterns for informed warehouse and inventory decisions (Amponsah *et al*., 2025; Crockett *et al*., 2023).

5. Foster Innovation and Competitiveness: AI facilitates product development and enables SMEs to adapt to shifting market dynamics, thereby gaining a competitive edge by staying ahead of competitors and unlocking new opportunities for growth (Al-Amin *et al*., 2024; Tanti, 2025; Iyelolu*et al*., 2024; Amponsah *et al*., 2025; Badghish& Soomro, 2024). AI in Marketing (AIM) has been empirically shown to significantly improve the performance of small businesses across financial, customer, internal business process, and learning and growth dimensions (Abrokwah-Larbi &Awuku-Larbi, 2024; Sánchez *et al*., 2025).

6. Enable Scalability: Automation allows SMEs to manage increased workloads without requiring proportional increases in workforce size, ensuring operational effectiveness even as the business expands (Al-Amin *et al*., 2024).

Collectively, these benefits position SMEs for sustainable growth, long-term resilience, and an enhanced ability to compete effectively in an increasingly digital and fast-paced marketplace (Iyelolu*et al*., 2024).

Although AI offers significant benefits, small and medium-sized enterprises (SMEs) face distinct challenges that set their adoption journey apart from that of larger organizations. These challenges often include limited financial resources, a lack of technical expertise, poor data quality and accessibility, and organizational resistance to change (Ayinaddis, 2025; Kapoor, 2024; Schlegel *et al*., 2023; Tawil *et al*., 2024; Iyelolu *et al*., 2024; Sánchez *et al*., 2025; Amponsah *et al*., 2025; Baez &Igbekele, 2021). Given these limitations, SMEs often prioritize easy-to-use, plug-and-play AI solutions that require minimal training and do not depend heavily on specialized skills (Ayinaddis, 2025; Hamdan *et al*., 2022b; Vedapradha *et al*., 2024; Sharma *et al*., 2022; Hansen & Bøgh, 2021).

Unlike larger firms that can more easily absorb the significant fixed costs associated with AI investment and typically possess extensive, well-structured data, SMEs often struggle with obtaining and managing the vast data volumes necessary for effective AI applications (Filippucci *et al*., 2024; Calvino and Fontanelli, 2023; Ayinaddis, 2025; Peretz-Andersson *et al*., 2024). The current academic literature also reflects a recognised lack of comprehensive comparative insights across firm sizes regarding AI adoption, as existing research often focuses exclusively on either SMEs or large firms (Ayinaddis, 2025; Amaugo, 2024; Baez & Igbekele, 2021; Zhan *et al*., 2024). This highlights a crucial area for further empirical investigation into the specific adoption, challenges, and impact of AI-powered workflow automation within the SME context.

While AI-powered workflow automation offers substantial advantages, small businesses often encounter greater obstacles to adoption than their larger counterparts. Common barriers include underdeveloped digital infrastructure, restricted budgets, limited access to technical expertise, and concerns regarding data security and ethical implementation. Furthermore, existing empirical literature often fails to capture nuanced adoption patterns and measurable outcomes specific to SMEs across various sectors, leading to a fragmented understanding of AI's impact on performance metrics like productivity, cost-efficiency, and innovation (Amponsah *et al*., 2025). This gap calls for a targeted investigation into the adoption process, barriers, and outcomes of AI workflow automation in SMEs.

The objectives of the study are to examine the extent and patterns of AI-powered workflow automation adoption among small businesses; to identify and categorize key internal and external barriers to adoption; to assess the impact of AI adoption on specific business outcomes (productivity, cost-efficiency, innovation); and to propose a contextually appropriate framework to support AI adoption in SMEs.

Theoretically, this study will address a noticeable gap in existing research on the adoption of AI-powered workflow automation by small and medium-sized enterprises (SMEs). Much of the current literature tends to focus on larger organizations, offering limited perspective on the unique challenges and adoption processes experienced by smaller firms (Ayinaddis, 2025; Baez & Igbekele, 2021). Additionally, there is a shortage of comprehensive frameworks that are specifically adapted to the realities of SMEs, including their limited resources, implementation hurdles, and the need to ensure ethical and responsible use of AI. By drawing on recent scholarly work and grounding the analysis in the Technology-Organization-Environment (TOE) framework and the Resource-

Based View (RBV), this study seeks to offer a clearer, more practical roadmap for SMEs pursuing strategic and sustainable AI adoption.

Practically**,** the findings will support SME leaders, policymakers, and technology providers by highlighting realistic adoption pathways, identifying actionable strategies, and recommending a phased roadmap to AI implementation. The study offers practical recommendations, including the use of affordable AI tools, investment in workforce training, attention to ethical concerns, and the promotion of public-private collaboration to help overcome adoption challenges. It also adds to the broader policy discussion on accelerating AI adoption among SMEs, particularly in emerging economies.

2. Literature Review

Artificial Intelligence (AI) is significantly changing how businesses operate, creating transformative opportunities, particularly for small and medium-sized enterprises (SMEs). Understanding workflow automation and the specific factors that shape AI adoption in SMEs is essential to unlocking its full potential.

2.1 The Concept of Workflow Automation

Workflow automation is a technological strategy that leverages programmed instructions and automated feedback systems to streamline business operations. It aims to reduce human error, eliminate repetitive tasks, and enhance overall efficiency. Artificial Intelligence (AI) plays a crucial role in advancing these objectives by enabling more intelligent and adaptive forms of automation (Al-Amin *et al*., 2024).

2.1.1 AI supports various types of automation, including

1. Task automation: This implies the use of AI to execute routine, rule-based activities traditionally performed by humans. Common applications in SMEs include data entry, invoice processing, inventory management, and customer service inquiries, which are characterised by low complexity and rapid return on investment (Sánchez *et al*., 2025; Al-Amin *et al*., 2024; Ikpe, 2024; Amponsah *et al*., 2025). Robotic Process Automation (RPA), a key enabling technology, leverages structured data and predefined rules to streamline these operations, thereby enhancing efficiency and allowing human workers to focus on higher-value strategic tasks (Bala *et al*., 2024; Tanti, 2025).

2. Process automation: This involves the end-to-end optimisation of business workflows rather than isolated tasks. AI facilitates this by enabling the automation of complex business-to-business (B2B) functions, including marketing target identification, customer relationship management, and supply chain coordination (Al-Amin *et al*., 2024). Through data-driven analysis, AI algorithms map existing processes, detect inefficiencies, and recommend streamlined pathways, resulting in enhanced operational coherence, reduced errors, and improved overall performance across business functions (Tanti, 2025).

3. Cognitive automation (Intelligent Automation): Unlike rule-based automation, it integrates process redesign, machine learning, and decision-making capabilities to optimise workflows dynamically and enhance productivity (Sánchez *et al*., 2025; McKinsey, 2019).

2.2 Role of AI Technologies in Workflow Automation

Artificial Intelligence (AI) encompasses systems capable of mimicking human intelligence to independently perform tasks, enhance productivity, and drive operational efficiencies (Filippucci *et al*., 2024; Brynjolfsson *et al*., 2023; Furman & Seamans, 2019; Ayinaddis, 2025). Workflow automation is enabled through key AI technologies:

- *Machine Learning (ML):* ML algorithms process large datasets to discover patterns, make predictions, and enhance decision-making without needing specific instructions for every task. Applications include predictive maintenance, demand forecasting, and inventory optimisation, contributing to improved supply chain efficiency (McKinsey, 2019; Iyelolu*et al*., 2024).
- *Natural Language Processing (NLP):* NLP allows systems to understand and generate human language, enabling the automation of communication tasks such as customer service interactions, document processing, and content generation (Bala *et al*., 2024; Al-Amin *et al*., 2024; Iyelolu*et al*., 2024).
- *Robotic Process Automation (RPA):* RPA handles routine, rule-based tasks such as processing invoices and fulfilling orders, helping to streamline operations and reduce manual effort. When integrated with ML and NLP, it can handle more complex workflows, reduce errors, and increase overall efficiency (Al-Amin *et al*., 2024; Tanti, 2025).
- *Predictive Analytics*: By leveraging AI to examine past data and forecast future trends, predictive analytics aids in strategic planning,

efficient resource allocation, and effective risk management.

- Computer Vision: Applied in quality control and document digitisation, computer vision enables machines to interpret visual inputs, enhancing process accuracy and speed.

Together, these technologies lay the groundwork for AI-powered workflow automation, helping SMEs enhance efficiency, adapt more quickly, and stay competitive in fast-changing business landscapes.

2.3 AI Adoption in Small Businesses

Although artificial intelligence (AI) offers significant opportunities to boost efficiency, improve decision-making, enhance customer engagement, and strengthen competitiveness, small and medium-sized enterprises (SMEs) often lag behind larger firms in terms of digital maturity. Digital maturity reflects a company's ability to effectively use digital tools to streamline operations, deliver value, and adapt to change. Many SMEs struggle to reach this level due to various structural, financial, and technological challenges.

A significant proportion of SMEs still depend on manual processes and fragmented, non-integrated data systems, which inhibit scalability and reduce their ability to compete effectively in increasingly data-driven markets (Al-Amin *et al*., 2024). Limited access to robust digital infrastructure, combined with inadequate internal technical expertise, further restricts their capacity to adopt and integrate advanced AI applications (Ayinaddis, 2025; Kapoor, 2024; Schlegel *et al*., 2023; Tawil *et al*., 2024). These challenges are compounded by concerns related to cybersecurity, data privacy, and the ethical implications of AI, which often remain unaddressed due to resource constraints (Iyelolu*et al*., 2024; Amponsah *et al*., 2025).

Moreover, many SMEs lack structured training programs or internal capabilities to support AI adoption and usage (Sánchez *et al*., 2025). In contrast to larger firms, which typically have dedicated teams and financial resources to explore and implement emerging technologies, SMEs frequently operate with limited human and capital resources. As a result, their technology adoption strategies are often reactive and focused on immediate, operational-level concerns rather than long-term digital transformation.

Nevertheless, SMEs possess certain strategic advantages that can facilitate AI adoption if adequately supported. Their smaller size and flatter hierarchies typically confer greater organizational agility and faster decision-making processes, enabling quicker adaptation when appropriate technologies are introduced (Ayinaddis, 2025; Sánchez *et al*., 2025). This flexibility, along with their close customer relationships and quicker feedback cycles, enables SMEs to adapt swiftly to shifting market demands and explore AI solutions focused on enhancing customer experiences.

In practice, SMEs tend to favour low-complexity, user-friendly AI tools that deliver clear, short-term value. These include chatbots for customer support, automated inventory management systems, and basic data analytics platforms (Ayinaddis, 2025; Al-Amin *et al*., 2024). "Plug-and-play" solutions that require minimal training or specialist knowledge are particularly attractive due to existing skill gaps and time constraints. While these technologies may not represent deep digital transformation, they often serve as critical entry points for broader AI integration, particularly in resource-constrained environments.

Importantly, empirical studies reveal that digital maturity in SMEs is not solely determined by firm size or sector, but is also influenced by managerial attitudes, strategic orientation, and openness to innovation (Jalil *et al*., 2024). SMEs that demonstrate proactive leadership and a future-focused approach to technology tend to show greater readiness for AI adoption, even when faced with infrastructure or financial constraints. This underscores the importance of context-specific strategies that combine affordable technology with accessible training and policy support.

In summary, the digital maturity of SMEs is marked by a paradox: while they face substantial barriers to AI adoption, they also exhibit characteristics that make them uniquely positioned to benefit from targeted, well-supported digital interventions. Bridging this maturity gap requires not only technological infrastructure but also human capital development, policy incentives, and sustained ecosystem collaboration to ensure inclusive AI-driven growth across the business spectrum.

AI adoption in small businesses is shaped by a variety of internal and external factors, commonly examined using models like the Technology-Organization-Environment (TOE) framework and components of the Diffusion of Innovations (DOI) theory. The TOE framework, in particular, is widely applied to study technology uptake, including AI, by focusing on three interconnected areas: technological readiness, organisational capability, and external environmental pressures. Its relevance in the SME context is well-supported by both empirical evidence and theoretical research (Sánchez *et al*., 2025; Ayinaddis, 2025).

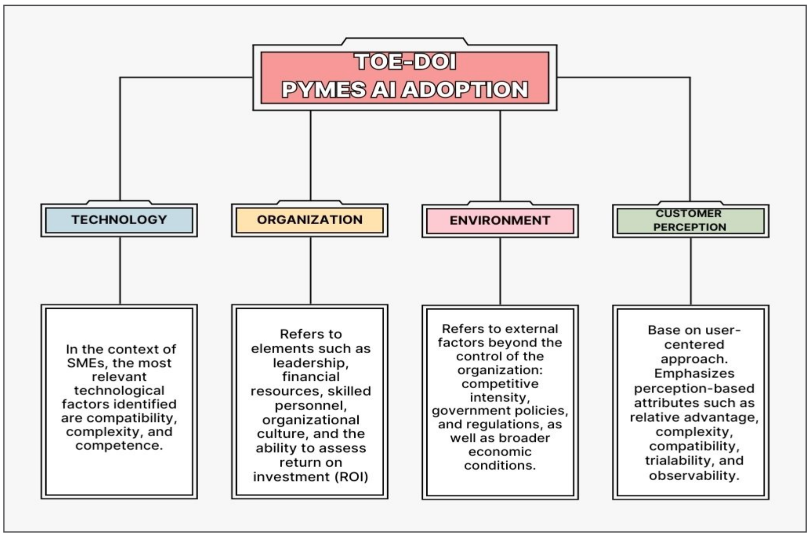

Figure 1. *Illustrative TOE–DOI Dimensions, factors, and attributes for AI adoption in SMEs*

Source: *Sanchez et al. (2025)*

These dimensions outlined in the figure 1 above can be expatiated as follows:

2.4 Technological Factors

These relate to the characteristics of the AI technology itself and the firm's existing technological infrastructure.

Compatibility describes the extent to which AI solutions integrate smoothly with an SME's current systems, including hardware, software, and operational workflows. When compatibility is high, it greatly encourages AI adoption by reducing friction. On the other hand, low compatibility can result in costly and time-intensive adjustments (Sánchez *et al*., 2025).

Complexity describes how difficult AI technology is to understand and use. AI is inherently complex, incorporating heterogeneous computing and machine learning. This presents a fundamental barrier to adoption for SMEs that often lack insightful knowledge resources. Consequently, SMEs tend to favour simpler, off-the-shelf AI solutions such as chatbots (Badghish & Soomro, 2024; Sánchez *et al*., 2025).

Technological competence, often referred to as technological readiness, reflects how well an SME's current technological setup can support the implementation of AI. This includes both physical assets like IT infrastructure and intangible elements such as past experience with technology and in-house expertise (Sánchez *et al*., 2025). Readiness is closely tied to the level of digital maturity and the robustness of IT systems (Ayinaddis, 2025; Brătucu *et al*., 2024). When choosing AI tools, SMEs tend to prioritise ease of use, favouring simple, plug-and-play solutions that require minimal technical effort (Ayinaddis, 2025).

A major technological barrier to successful AI adoption is the lack of sufficient, high-quality, and well-integrated data. Many SMEs struggle to manage the large volumes of data required for effective AI implementation (Sánchez *et al*., 2025; Ayinaddis, 2025; Kovič *et al*., 2024; Peretz-Andersson *et al*., 2024; Tawil *et al*., 2024). This challenge is compounded by infrastructure constraints and difficulties integrating AI with older, legacy systems, which further limit adoption efforts (Al-Amin *et al*., 2024; Sánchez *et al*., 2025).

2.5 Organisational Factors

These relate to the firm's internal context, including its structure, resources, and culture. Skills and competencies are critical, as functional and operational knowledge creates significant differences between SMEs and larger firms (Ayinaddis, 2025; Grashof & Kopka, 2023; Wei & Pardo, 2022). Small firms often lack the necessary expertise and may not be able to offer competitive salaries to attract skilled talent (Ayinaddis, 2025; Sánchez *et al*., 2025). The absence of skilled staff and internal advocates poses a significant obstacle to AI adoption in SMEs. To build internal capacity, it is essential to invest in ongoing, role-specific training that covers data analysis, core AI concepts, and algorithmic thinking.

Financial constraints, characterised by high initial investments, ongoing maintenance costs, and uncertainty about returns, significantly hinder AI implementation in SMEs (Iyelolu*et al*., 2024; Sánchez *et al*., 2025; Amponsah *et al*., 2025). However, findings from some contexts, such as Saudi Arabian SMEs, suggest that implementation costs may not always be a significant barrier, indicating possible availability of financial resources for technology investment.

Organisational culture and leadership support are also essential. Resistance to change, rigid hierarchies, limited exposure to digital tools, and fear of job displacement can impede AI adoption (Iyelolu *et al*., 2024; Sánchez *et al*., 2025; Amponsah *et al*., 2025). Conversely, an innovative CEO and management's understanding of new technologies are vital for successful implementation (Baez and Igbekele, 2021; Kumar *et al*., 2022; Amponsah *et al*., 2025). A lack of managerial awareness or a perception of high costs can further hinder adoption.

Organisational culture and resistance to change present significant hurdles, especially since adopting AI typically requires substantial modifications to established workflows. Employees may worry about losing their jobs or seeing their responsibilities diminished. To overcome these challenges, it's crucial to implement effective change management strategies, maintain open and transparent communication, and actively involve staff in the adoption journey. These steps help foster a culture that embraces innovation and remains adaptable in the face of technological change.

2.6 Environmental Factors

Environmental factors refer to the external conditions shaping a firm's operations, including market trends, institutional support, and regulatory frameworks. These elements are a core part of the Technology–Organization–Environment (TOE) framework and are often enriched by perspectives from the Technology Acceptance Model (TAM), which emphasises the importance of perceived usefulness and ease of use in driving technology adoption (Alabi, 2025).

Market and competitive pressures play a key role in driving AI adoption, especially as SMEs aim to stay agile and responsive in fast-changing environments. The need to remain competitive often motivates businesses to implement AI solutions that boost operational efficiency and improve customer service.

In addition, government support and strategic partnerships serve as important enablers. Financial incentives like grants, subsidies, and low-interest loans can ease budgetary limitations and encourage SMEs to invest in AI technologies. Furthermore, collaboration with universities, research centres, and external consultants or vendors facilitates knowledge transfer, provides technical assistance, and enhances SMEs' capacity for AI integration (Ayinaddis, 2025). Partner collaboration has been shown to significantly increase the likelihood of successful AI adoption.

Regulatory compliance is becoming increasingly critical, particularly in areas like data protection, privacy, and the responsible use of AI. SMEs must navigate these regulations carefully to avoid legal risks and ensure ethical implementation of AI technologies. Larger firms typically have more established mechanisms to meet regulatory demands and align with ethical practices, whereas SMEs often lack such infrastructure (Ayinaddis, 2025). The absence of clear AI guidelines and robust data governance structures presents a challenge to adoption. To address this, SMEs are encouraged to establish lightweight but effective ethical governance frameworks to ensure transparency, build stakeholder trust, and sustain responsible AI practices.

Within the TAM framework, SMEs assess AI tools based on how easily they can be integrated into existing workflows and the perceived value they add to productivity, decision-making, and customer engagement (Alabi, 2025). This perception is crucial, especially in resource-constrained environments, where tools must demonstrate immediate and tangible benefits to justify adoption.

2.7 Diffusion of Innovations (DOI) Theory

The Diffusion of Innovations (DOI) theory complements the Technology–Organization–Environment (TOE) framework by exploring how new technologies are adopted and spread within a social system. It highlights key attributes of innovation such as relative advantage, compatibility, complexity, trialability, and observability, offering insight into how individuals and organisations assess and embrace emerging technologies (Sánchez *et al*., 2025). For example, relative advantage, which refers to the belief that a new solution provides better outcomes than existing practices, plays a major role in encouraging AI adoption.

In essence, AI adoption in SMEs is not simply a technical upgrade but a strategic transformation. It demands thoughtful consideration of technological preparedness, internal capabilities, leadership engagement, organisational culture, and external institutional support. Similar to a gardener preparing the soil before planting, SMEs must ensure that their technological, organisational, and environmental conditions are well aligned for AI to take root and thrive, leading to sustained improvements in efficiency and innovation.

2.8 Challenges Faced by Small Businesses

It has been established that small businesses contributes significantly in the livelihood of a family (Akinloye, 2024a; Akinloye, 2024b; Akinloye, 2025), community, and nation at large. Hence, it must be thoroughly monitored and driven so that the business will grow into the unforeseeable future. The growing integration of Artificial Intelligence (AI) into business operations represents a major shift, unlocking transformative opportunities across various sectors. While large companies often have the resources and infrastructure to adapt easily to this change, small and medium-sized enterprises (SMEs) face specific challenges, even though they can also benefit greatly from AI adoption. Exploring these dynamics is vital for advancing academic understanding and supporting practical, strategic decision-making particularly within rigorous scholarly contexts.

2.9 Challenges Faced by Small and Medium-sized Enterprises in AI Adoption

The adoption of AI by SMEs is hindered by a multifaceted array of obstacles, broadly categorised into technical, financial, organisational, and regulatory/ethical concerns. These challenges are often exacerbated by the inherent characteristics of smaller firms, such as their limited resources and comparatively simpler organisational structures (Ayinaddis, 2025; Iyelolu*et al*., 2024; Sánchez *et al*., 2025).

A primary technical impediment for SMEs lies in their inadequate technological infrastructure and data readiness (Ikpe, 2024; Amponsah *et al*., 2025; Sánchez *et al*., 2025). AI systems are data-intensive, requiring vast volumes of high-quality, well-integrated data for effective training and deployment (Fu *et al*., 2023; Sánchez *et al*., 2025). However, many SMEs struggle with obtaining, managing, and maintaining such datasets, often lacking the necessary infrastructure for data collection, storage, and processing (Ayinaddis, 2025; Amponsah *et al*., 2025; Peretz-Andersson *et al*., 2024). Fragmented data architectures, poor data standardisation, and a lack of interoperability further complicate AI development and decision-making processes (Sánchez *et al*., 2025). Moreover, the inherent complexity of AI technologies themselves, combining heterogeneous computing and machine learning components, poses a substantial barrier, especially for firms lacking specialised knowledge (Amponsah *et al*., 2025; Badghish& Soomro, 2024). The "AI Hype" can also lead to an unclear definition of the technology and false expectations, contributing to challenges in its adoption (Baez &Igbekele, 2021).

Financial constraints represent another significant hurdle for SMEs (Al-Amin *et al*., 2024; Amponsah *et al*., 2025; Ikpe, 2024; Iyelolu*et al*., 2024). The initial investment required for AI development, purchase, integration, and ongoing maintenance can be prohibitively expensive for businesses operating on tighter budgets (Alabi, 2025; Iyelolu *et al*., 2024; Ransbotham *et al*., 2017; Sánchez *et al*., 2025). This challenge is often compounded by limited access to external funding or loans (Amponsah *et al*., 2025; Bąk *et al*., 2024; Nagy *et al*., 2023; Tominc *et al*., 2024). The uncertainty surrounding the return on investment (ROI) and long payback periods for AI initiatives also contributes to delayed decision-making and heightened risk aversion among SMEs (Sánchez *et al*., 2025; Zhan *et al*., 2024). While some regions, such as Saudi Arabia, demonstrate that cost may not be a primary barrier for their SMEs due to sufficient financial capabilities (Badghish & Soomro, 2024), this remains a widespread issue globally.

From an organisational perspective, the shortage of skilled personnel and technical expertise is a critical barrier (Amaugo, 2024; Ayoade *et al*., 2021; Baez & Igbekele, 2021; Ikpe, 2024; Iyelolu *et al*., 2024; Sánchez *et al*., 2025). SMEs often struggle to attract and retain individuals with the necessary skills in machine learning, data science, and software engineering due to their inability to offer competitive salaries and career growth opportunities comparable to larger firms (Amponsah *et al*., 2025; Peretz-Andersson *et al*., 2024; Baez & Igbekele, 2021; Gartner, 2018; Sánchez *et al*., 2025). This skill gap can severely impede the effective deployment and utilisation of AI solutions (Bughin *et al*., 2017). Furthermore, resistance to change and a lack of organisational support can significantly hinder AI adoption (Alabi, 2025; Amponsah *et al*., 2025; Iyelolu *et al*., 2024; Tanti, 2025). Employees may fear job displacement, while rigid organisational cultures and leadership styles can discourage creativity, risk-taking, and knowledge sharing, leading to a lack of awareness of AI opportunities (Amponsah *et al*., 2025; Iyelolu *et al*., 2024). While smaller organisations might exhibit greater agility in change management than larger ones (Baez &Igbekele, 2021), a clear AI strategy and managerial understanding of AI benefits are crucial for successful implementation (Alabi, 2025; Baez & Igbekele, 2021).

Finally, regulatory and ethical concerns pose increasingly complex challenges (Alabi, 2025; Amponsah *et al*., 2025; Tanti, 2025). Data privacy and security are paramount, particularly given the vast amounts of sensitive data processed by AI systems, and SMEs often lack the robust cybersecurity measures of larger enterprises (Al-Amin *et al*., 2024; Iyelolu *et al*., 2024; Tanti, 2025). Ensuring compliance with evolving data protection regulations, such as GDPR, is a significant burden (Al-Amin *et al*., 2024; Iyelolu *et al*., 2024; Tanti, 2025). Moreover, the potential for algorithmic bias and fairness issues, where AI models perpetuate existing societal biases if trained on unrepresentative data, raises profound ethical questions in applications like hiring or credit scoring (Alabi, 2025; Amponsah *et al*., 2025; Tanti, 2025). The lack of clear governance policies and ethical frameworks within SMEs makes navigating these complexities particularly challenging (Amponsah *et al*., 2025; Sánchez *et al*., 2025).

2.10 Impact of AI on Business Performance in SMEs

Despite the formidable challenges, AI offers substantial opportunities for SMEs to enhance their business performance across various dimensions. The overarching benefits often manifest as improved operational efficiency, cost savings, enhanced customer experience, and superior decision-making capabilities, ultimately fostering a stronger competitive advantage (Al-Amin *et al*., 2024; Ikpe, 2024; Iyelolu *et al*., 2024; Amponsah *et al*., 2025; Tanti, 2025).

AI-driven workflow automation significantly increases operational efficiency and productivity by streamlining processes and automating repetitive, mundane tasks such as data entry, inventory management, and customer service inquiries (Al-Amin *et al*., 2024; Ikpe, 2024; Amponsah *et al*., 2025; Sánchez *et al*., 2025). This not only minimises human error but also frees up human capital for more strategic and creative endeavors (Al-Amin *et al*., 2024; Iyelolu*et al*., 2024; Tanti, 2025). Empirical evidence suggests that AI applications can improve performance beyond traditional analytics techniques (Phalin & Kaniyar, 2017), contributing to higher effectiveness and overall productivity within organisations (Ayinaddis, 2025).

These efficiency gains translate directly into substantial cost savings for SMEs (Al-Amin *et al*., 2024; Ikpe, 2024; Iyelolu*et al*., 2024; Amponsah *et al*., 2025; Tanti, 2025). For instance, AI-powered inventory management systems can reduce stockouts and overstocking, while predictive maintenance systems can foresee equipment failures, thereby reducing downtime and associated expenses (Ikpe, 2024; Iyelolu *et al*., 2024). Such optimisations directly impact the bottom line, allowing SMEs to allocate resources more strategically (Iyelolu*et al*., 2024).

AI also profoundly enhances customer experience and engagement (Iyelolu*et al*., 2024; Amponsah *et al*., 2025; Tanti, 2025). AI-powered chatbots and virtual assistants can provide 24/7 support, reduce response times, and handle high volumes of customer inquiries, improving satisfaction and loyalty (Al-Amin *et al*., 2024; Ikpe, 2024; Sánchez *et al*., 2025; Tanti, 2025). AI-driven recommendation engines and personalised marketing strategies enable businesses to offer tailored product suggestions and content based on customer behaviour, strengthening brand loyalty and driving sales (Tanti, 2025).

Crucially, AI empowers SMEs with improved decision-making capabilities through predictive analytics and real-time insights (Al-Amin *et al*., 2024; Ikpe, 2024; Iyelolu*et al*., 2024; Amponsah *et al*., 2025; Tanti, 2025). AI algorithms can analyse vast datasets to identify patterns, forecast trends, and predict customer behaviour, enabling businesses to make data-driven decisions swiftly and with greater confidence (Al-Amin *et al*., 2024; Ikpe, 2024; Iyelolu*et al*., 2024; Sánchez *et al*., 2025). This analytical capability allows for more effective resource allocation, optimisation of pricing strategies, and better risk management (Iyelolu*et al*., 2024; Amponsah *et al*., 2025).

These operational and strategic improvements collectively contribute to a heightened competitive advantage and scalability for SMEs (Al-Amin *et al*., 2024; Ikpe, 2024; Iyelolu *et al*., 2024). AI enables businesses to adapt quickly to market fluctuations and demand shifts (Al-Amin *et al*., 2024). For instance, in business-to-business (B2B) marketing, AI integration can enhance innovation by increasing lead generation capabilities (Zhan *et al*., 2024). AI adoption is not merely a technological upgrade but a strategic lever for transformation, essential for maintaining relevance in an increasingly digital and competitive marketplace (Sánchez *et al*., 2025). Firms implementing AI for B-2-B marketing have empirically been shown to receive greater stock returns than their industry peers without AI implementation (Zhan *et al*., 2024). AI facilitates innovation by fostering continuous product improvement and enabling the development of new value creation pathways (Iyelolu*et al*., 2024; Sánchez *et al*., 2025; Zhan *et al*., 2024).

2.11 Gaps in Measuring Intangible Impacts

While quantitative metrics like stock returns (Zhan *et al*., 2024), sales increases, and downtime reductions

(Haider & Faisal, 2024; Wan *et al*., 2020) provide clear indications of AI's financial and operational impact, there remain significant gaps in comprehensively measuring intangible impacts. Metrics such as employee satisfaction, increased innovation capacity, or long-term brand reputation, though acknowledged as benefits (Alabi, 2025; Iyelolu*et al*., 2024), are not always easily quantifiable with existing methodologies (Zhan *et al*., 2024).

The financial benefits of AI are often difficult to assess in the short term, as they are influenced by factors such as managerial planning and shifting market conditions (Zhan *et al*., 2024). Although AI is widely associated with improvements in productivity and innovation, these gains are not always immediately measurable in terms of long-term net value, especially when the full costs of adoption and ongoing use are taken into account (Sánchez *et al*., 2025). This points to a clear need for future research that incorporates more detailed qualitative and longitudinal methods to capture the wider and less tangible impacts of AI. Such studies can offer a more holistic understanding of AI's effect on organisational performance and sustained growth.

AI represents a complex yet promising avenue for SMEs to achieve lasting growth and competitiveness. To realise this potential, SMEs must overcome a range of technical, financial, and organisational challenges, while also addressing regulatory and ethical concerns. By using AI strategically to enhance efficiency, reduce operational costs, improve customer engagement, and support data-driven decision-making, SMEs can strengthen their position in an increasingly digital economy. The process of adopting AI is not simply a technical upgrade but a strategic necessity that requires a thoughtful, customised approach to unlock its full impact.

2.12 Conceptual Framework

A well-rounded conceptual framework that combines the Technology-Organization-Environment (TOE) model with the Resource-Based View (RBV) provides a strong foundation for examining the complex factors influencing Artificial Intelligence (AI) adoption, especially among Small and Medium-sized Enterprises (SMEs). This integrated perspective helps to fill existing gaps in the literature, which tends to concentrate on large corporations and often overlooks the unique barriers and adoption behaviours characteristic of smaller firms (Ayinaddis, 2025; AI impact on SME, 2024; Zhan *et al*., 2024). Such a framework is crucial for developing tailored strategies that support sustainable and responsible AI integration in the SME context (AI impact on SME, 2024).

Table 1. *Applying the TOE Framework to Identify AI Adoption Barriers and Strategic Responses in SMEs*

TOE Dimension	Challenge	Key Actionable Solutions
Technological	Lack of data quality and access Infrastructure and system misalignment Scalability and complexity of AI tools Generative AI underutilization and lack of strategic alignment	Data governance, real-time data collection, cleaning,integration with APIs Cloud platforms, modular architectures,public-private AI centres Modular deployment, agile methodology, scalablecloud services Low-code Gen-AI tools,toward open-weight LLMadoption augmentation use cases, phased integration,innovation alignment
Organizational	Skills shortage and knowledge gap Cultural resistance and lack of innovation mindset Lack of structured methodology for AI adoption Financial resource constraints Human-AI misalignment in productivity goals Augmentation-focused adoption, co-intelligencemodels, upskilling, role redefinition Limited responsible AI governance and ethical practices.	Internal training, external partnerships, accessibleplatforms, open innovation Pilot projects, transparent leadership, learningenvironments, inclusive change management Six-phase roadmap/methodology: assess, definestrategy, select tools, pilot, train, monitor Flexible financing, pilot-based risk management,public incentives, cloud services Lightweight AI ethics protocols, transparency,employee awareness, stakeholder inclusion.
Environmental	Limited public-private collaboration andpolicy support.	Innovation ecosystems, collaborative hubs, AI grants,capacity-building programs.

The Technology-Organization-Environment (TOE) framework serves as a foundational theoretical model for understanding technology adoption within organisations (Sánchez *et al*., 2025; Badghish & Soomro, 2024). It posits that the adoption and implementation of technological innovations are influenced by three key contexts: technological, organisational, and environmental (Baker, 2012; Sánchez *et al*., 2025). This framework has received strong empirical and theoretical support in various contexts, including that of SMEs, proving effective in explaining technology implementation behaviour (Ayinaddis, 2025; Sánchez *et al*., 2025).

Within the technological context, AI adoption in SMEs is significantly influenced by the existing IT infrastructure and digital maturity (Ayinaddis, 2025; Sánchez *et al*., 2025). Large firms typically possess the advanced infrastructure and computing power necessary for extensive AI systems, leveraging substantial financial resources for training and deployment (Ayinaddis, 2025). In contrast, SMEs often face high barriers to accessing such infrastructure (Kapoor, 2024; Schlegel *et al*., 2023; Tawil *et al*., 2024; Ayinaddis, 2025; Ikpe, 2024). Issues such as data deficiency, poor data quality, and inadequate data governance are paramount, as AI systems rely heavily on large volumes of high-quality data (Ayinaddis, 2025; Sánchez *et al*., 2025). Furthermore, the complexity of AI technology itself, and its compatibility with existing, often fragmented, legacy systems, presents a significant hurdle for SMEs, which tend to favour user-friendly, "plug-and-play" solutions requiring minimal training (Ayinaddis, 2025; Sharma *et al*., 2022; Hansen & Bøgh, 2021; AI impact on SME, 2024).

The organisational context pertains to internal characteristics that either facilitate or impede AI adoption (Sánchez *et al*., 2025; Badghish& Soomro, 2024). A crucial element here is leadership support and awareness, as management commitment is vital for allocating resources and fostering an environment conducive to AI initiatives (Ayinaddis, 2025; Sánchez *et al*., 2025). However, some SME management teams may be resistant to AI adoption due to perceived high costs and long payback periods (Badghish& Soomro, 2024; Baez &Igbekele, 2021).

Financial constraints represent another critical barrier, with the initial and ongoing costs of AI software, hardware, data storage, and skilled personnel often being prohibitively expensive for SMEs (Iyelolu*et al*., 2024; Ayinaddis, 2025; Ola Al-Amin *et al*., 2024). The skills gap and lack of internal technical expertise are also major challenges, as SMEs often struggle to attract and retain talent capable of developing and maintaining AI solutions (Ayinaddis, 2025; Peretz-Andersson *et al*., 2024; Baez &Igbekele, 2021; Iyelolu*et al*., 2024). Furthermore, resistance to change among employees, stemming from fears of job displacement or altered roles, can hinder the smooth integration of new AI systems (Iyelolu*et al*., 2024; Baez &Igbekele, 2021).

Lastly, the environmental context encompasses external factors that can influence AI adoption (Sánchez *et al*., 2025; Badghish & Soomro, 2024). Competitive pressure often drives firms, including SMEs, to adopt AI to enhance efficiency and gain strategic advantage (Ayinaddis, 2025; Sánchez *et al*., 2025). Government support through monetary incentives, subsidies, and credit availability can significantly encourage AI adoption in SMEs, helping to overcome resource constraints (Badghish & Soomro, 2024; Iyelolu *et al*., 2024). However, regulatory and ethical concerns pose substantial challenges. Issues such as data privacy and security, compliance with regulations like GDPR, and the potential for bias in AI algorithms are critical considerations, especially as SMEs may lack the robust cybersecurity measures and dedicated ethical frameworks of larger firms (Ayinaddis, 2025; Iyelolu*et al*., 2024; Ikpe, 2024). The rapid evolution of AI technology also creates regulatory uncertainty, which can discourage adoption due to perceived compliance risks (OECD, 2024).

While the TOE framework offers a solid structural perspective on AI adoption, it falls short in addressing individual perceptions and the influence of sociocultural dynamics (Ayinaddis, 2025; Sánchez *et al*., 2025). The Resource-Based View (RBV) helps bridge this gap by emphasising the role of a firm's unique internal resources and capabilities. According to RBV, sustainable competitive advantage stems from assets that are valuable, rare, difficult to replicate, and not easily replaced (Abrokwah-Larbi &Awuku-Larbi, 2024). Applied to AI adoption, this perspective highlights how an organisation's tangible and intangible resources shape its capacity to adopt and effectively utilise AI technologies.

Tangible resources relevant to AI adoption include financial capital, robust IT infrastructure, and adequate computing power (Ayinaddis, 2025; Sánchez *et al*., 2025; Badghish& Soomro, 2024). SMEs are inherently limited in these areas, making AI investments a significant challenge (Iyelolu*et al*., 2024; Ayinaddis, 2025; Baez &Igbekele, 2021).

Intangible resources are equally, if not more, critical. These encompass technical expertise, skilled human capital, digital maturity, organisational culture, and absorptive capacity – the ability to recognise the value of new information, assimilate it, and apply it (Ayinaddis, 2025; Badghish& Soomro, 2024; Sánchez *et al*., 2025). The availability and quality of these intangible assets directly impact an SME's readiness to integrate AI solutions (Ayinaddis, 2025). For instance, a lack of skilled personnel within SMEs significantly hinders their ability to implement AI (Peretz-Andersson *et al*., 2024).

Conversely, strong management support and a culture that embraces experimentation and tolerates failure are key internal resources that promote AI adoption and innovation (Badghish & Soomro, 2024; Baez & Igbekele, 2021). AI itself can become a valuable resource, enabling enhanced operational efficiency, decision-making, and scalability, thereby contributing to a firm's competitive edge (Ola Al-Amin *et al*., 2024; Iyelolu*et al*., 2024; Tanti, 2025).

The combined conceptual framework that integrates the TOE model with the Resource-Based View (RBV) delivers a more complete and refined perspective on AI adoption within SMEs. TOE offers a broad macro- and meso-level analysis, capturing both external pressures and internal organisational factors that shape adoption decisions. In contrast, RBV brings a micro-level focus, examining the specific resources and capabilities that determine a firm's ability to effectively implement AI and achieve a competitive edge (AI impact on SME, 2024). For example, within TOE's "organisational context," RBV explains *why* financial constraints are a barrier (limited financial resources) and *how* a skills gap impacts adoption (lack of skilled human capital). Similarly, in the "technological context," RBV highlights the importance of proprietary data assets or advanced IT infrastructure as valuable resources. This combined perspective allows for an examination not only of whether a firm is ready for AI adoption (TOE's readiness assessment) but also whether it possesses the specific, unique resources necessary to convert AI into a sustainable competitive advantage (RBV's focus on inimitable resources). The integration of these frameworks also enables the inclusion of perceptual elements such as ease of use and compatibility, concepts often drawn from the Diffusion of Innovations (DOI) theory. This addition enriches the framework by capturing the informal and perception-driven nature of decision-making that is common among SMEs (Sánchez *et al*., 2025; Ayinaddis, 2025).

For Small and Medium-sized Enterprises, this combined framework is particularly relevant. SMEs typically operate with limited resources, streamlined organisational structures, and more centralised leadership, which makes a flexible and context-aware analytical approach essential for understanding their AI adoption dynamics (Ayinaddis, 2025; Sánchez *et al*., 2025). The framework helps to identify critical enablers and barriers unique to their size and operational context, highlighting areas where targeted support, such as accessible AI tools, government incentives, public-private partnerships, and focused training programs, is most needed (Ayinaddis, 2025; Iyelolu*et al*., 2024; AI impact on SME, 2024). It underscores that for SMEs, AI adoption is not merely a technological upgrade but a strategic imperative that requires careful management of internal capabilities and engagement with a supportive external ecosystem (Sánchez *et al*., 2025).

Consider this integrated framework as a blueprint for a complex machine. The TOE elements provide the overall design, showing the various interconnected systems (technological, organisational, environmental) that must align for the machine (AI adoption) to function. Meanwhile, the RBV elements inspect the quality and uniqueness of the internal components (resources like skilled talent, data, and financial capital), determining not just if the machine *can* be built, but how well it will perform and if it can outperform others in the long run. Without both aspects, one might either build a machine that fits its environment but lacks the internal power to excel, or one with great components but an incompatible external design, ultimately failing to deliver its full potential.

3. Methodology

This study adopts an observational cross-sectional research design based exclusively on secondary data analysis. No primary data collection was undertaken. Instead, the analysis utilizes microdata from the Flash Eurobarometer 537: Survey on the Use of Technologies by SMEs conducted in 2023 across 36 countries, including all 27 EU Member States and 9 non-EU countries. The design is descriptive-analytical and suitable for identifying adoption patterns, sectoral variations, and the barriers to AI-powered workflow automation among SMEs.

Given the scale and diversity of the dataset, comprising exactly 19,350 enterprises, this approach allows for robust, empirical insight into SME behaviour across industries and countries. The research focuses on describing the landscape of AI adoption, not inferring causality, which aligns with the observational nature of the dataset. This methodology aligns with existing literature on digital technology adoption using secondary firm-level survey data (Amponsah *et al*., 2025; Hunady, 2025; Adeniran, Asifat *et al*., 2024; Adeniran & Tayo-Ladega, 2024).

The study draws exclusively from the Flash Eurobarometer 537 microdata collected by the European Commission in 2023. This survey was designed to assess digitalisation, AI integration, and digital skills among SMEs. The dataset was accessed through the GESIS data portal and contains anonymised, publicly available firm-level responses.

Key features of the dataset include:

- Firm-level data on digital technologies, including AI-powered tools.
- Detailed business characteristics: sector (NACE_A), firm size, country, and location (urban/rural).
- Responses to both closed-ended and scaled items related to AI use, barriers, and skills.

The dataset is ideal for comparative sectoral analysis and is frequently cited in EU-wide policy and academic reports on digital transformation in SMEs.

3.1 Sampling and Inclusion Criteria

This study uses the OECD/Eurostat definition of small and medium-sized enterprises (SMEs), identifying them as businesses with fewer than 250 employees. From the original sample of 19,350 businesses, a subset of 17,197 enterprises met the SME size definition based on the size classification provided in the variable SIZE.

Only this filtered SME subset was used for analysis. This approachensures consistency and supports the study's aim to specifically examine automation dynamics within small businesses.

3.2 Country and Sector Coverage

The dataset includes firms from 36 countries. All were retained in the analysis to preserve cross-national comparability.

Sector (independent grouping variable): The variable NACE_A in the dataset indicates the broad industry sector of the firm, based on the NACE Rev. 2 classification. Each NACE_A code (1–12) corresponds to a major sector (NACE section) as follows:

NACE_A Code	Sector Description
1	Agriculture, forestry and fishing (NACE A)
2	Mining and quarrying (NACE B)
3	Manufacturing (NACE C)
4	Electricity, gas, steam and air conditioning; Water supply; waste management (NACE D–E)
5	Construction (NACE F)
6	Wholesale and retail trade; repair of motor vehicles (NACE G)
7	Transportation and storage (NACE H)
8	Accommodation and food service activities (NACE I)
9	Information and communication (NACE J)
10	Financial and insurance activities (NACE K)
11	Real estate activities (NACE L)
12	Professional, scientific and technical activities (NACE M)

Note: *For example, NACE_A code 2 corresponds to "Mining and quarrying," defined as the extraction of minerals (solids, liquids or gases) The NACE classification is defined by Eurostat (see NACE Rev.2 manuals), and these broad categories are used for industry segmentation in our analysis. The variable nace_a thus serves as a categorical independent variable to group firms by sector.*

3.3 Variable Definitions and Measurement

This study examines adoption, barriers, and impact in SMEs. We define and operationalize key constructs as follows:

3.4 Dependent Variable: AI-Powered Workflow Automation Adoption

We measure AI-powered automation adoption via binary and continuous indicators. For example, Eurobarometer asks firms if they use "Artificial Intelligence or machine learning tools in their operations," and provides related items (yes/no).

The central dependent variable is AI adoption, captured through responses to Question Q10, which asks:

"Has your company adopted at least one of the following technologies?" ... including "Artificial Intelligence (e.g. tools that simulate human intelligence, machine learning, etc.)"

A binary variable was created:

1 = AI adopted, if the respondent selected "Artificial Intelligence".

0 = AI not adopted, otherwise.

This allows for categorical comparisons (e.g. AI vs non-AI adopters) and facilitates descriptive disaggregation across sectors, sizes, and regions.

3.5 Barriers to Adoption (Independent Variables/ Mediators)

Key barriers include skill shortages, high costs, inadequate infrastructure, and regulatory hurdles, issues commonly cited for SMEs. Both surveys contain items on perceived obstacles: e.g. "lack of skilled staff" or "cost of technology" rated on a Likert or yes/no basis. We will code each barrier as binary or ordinal, and may apply factor analysis to identify underlying dimensions (e.g. "human capital constraints" factor, "financial constraint" factor).

These serve as independent variables explaining adoption. In mediation analysis, we may treat barrier factors as mediators between country context and adoption outcomes.

3.6 Firm Performance (Dependent Variable)

To assess impact, we use firm-level performance metrics from the surveys. Typical measures are year-over-year sales growth, labour productivity (value-added per worker), export status, or return on assets. Eurobarometer include self-assessed performance improvements. We will analyse how AI adoption (and ease of adoption) predicts these outcomes, controlling for other factors.

3.7 Control and Context Variables

We include standard controls to isolate effects. At the firm level: size (number of employees), age, ownership (foreign vs domestic), and sector (industry dummies). At the country/region level: GDP per capita, broadband penetration, and an AI-readiness index. These account for economic and institutional context.

All measures are grounded in prior research. For instance, defining SMEs by headcount aligns with OECD norms, and using logistic regression on a binary adoption variable follows Hunady (2025). We ensure construct validity by matching survey questions to theoretical concepts (e.g. TOE framework factors for technology adoption). Any indices (e.g. a "barrier score") will be tested for reliability (Cronbach's alpha) before use. Where possible, we treat variables consistently across datasets (e.g. rebasing growth rates) to allow comparable analysis.

3.8 Analytical Techniques

Both quantitative and qualitative methods were employed, and integrated through triangulation.

3.9 Descriptive Analysis

First, we will compute summary statistics of adoption rates, barrier frequencies, and performance metrics. This includes cross-tabulations by country, sector, and firm-size to reveal patterns. We will visualize these with charts and maps to identify trends and hotspots. This sets the stage and confirms the basic landscape of SME automation adoption across contexts.

3.10 Quantitative Modelling

For hypothesis testing and multivariate analysis, we will primarily use regression techniques. We plan a two-stage modelling approach:

1. *Adoption Model (Logistic Regression):* The dependent variable is binary (AI adoption). Independent variables include firm size, sector, age, country-level controls, and barrier measures. A logistic (or probit) regression will estimate the odds of an SME adopting AI, given its characteristics and this mirrors prior studies that used logistic models to identify adoption correlate. Coefficients on barriers will reveal which obstacles significantly deter adoption, addressing the research objective on barriers. We will cluster standard errors by country to account for intra-country correlations.
2. *Impact Model (Linear Regression/SEM):* For performance outcomes (continuous growth or productivity), we will regress these on adoption status and other covariates. We may use OLS or (if necessary) multilevel linear models if data are nested (firms in countries). This model estimates the effect of having adopted AI on performance, controlling for confounders. If our conceptual model suggests mediation (e.g. skilled workforce mediating AI → performance), we will test that via path analysis or structural equation modelling.

Throughout, we will check for collinearity, heteroskedasticity, and fit, and may include interaction terms (e.g. adoption × country technology index) to test conditional effects.

3. *Qualitative Analysis:* The quantitative models will be complemented by qualitative content analysis. For instance, if the Eurobarometer include open-

ended responses on "main obstacle," we will code those text answers thematically (using an inductive coding approach) to identify common themes (e.g. "fear of complexity," "lack of trust in AI"). Even without open text, we can qualitatively examine how questionnaire items frame the issue. We will use thematic analysis techniques (coding transcripts and identifying patterns) to enrich understanding of SME attitudes and challenges. This helps interpret the statistical findings and may surface nuances not captured by numeric variables.

4. *Triangulation:* We will integrate quantitative and qualitative insights to strengthen conclusions. For example, if regression shows "lack of skilled labour" as a significant barrier, we will corroborate it with frequency of that theme in open responses. Country-level ICT indicators from the OECD data will be used to contextualize firm-level trends (e.g. a country's low broadband rate might explain low AI adoption in its firms). Through such cross-validation, we enhance validity.

All analyses will be conducted in standard statistical software using R and qualitative coding software NVivofor transparency and reproducibility. Results will be checked for robustness via sensitivity tests (e.g. alternative variable definitions, sub-sample analysis of SMEs by size class).

4. Results

4.1 Descriptive Results

This section presents the descriptive statistics and adoption patterns of AI-powered workflow automation among SMEs, based on the Flash Eurobarometer 537 microdata. (A secondary data that contain 18,388 total respondent from 27 EU and 9 other countries and 14,870 analysed as fitted as SMEs based on number of employee).

4.2 Profile of Participating Businesses

Total number of SME respondents analyzed: 14870

SMEs were categorized by size as follows:

Table 2. *Frequency of SMEs categories (Flash Eurobarometer 537 microdata)*

Size Category	Frequency
Micro	7745
Small	7125

The largest share of respondents (weighted) are in services sectors (47.1%), followed by retail/trade (26.3%), industry (17.5%), and manufacturing (9.1%).

Table 3. *Frequency of SMEs sector categories (Flash Eurobarometer 537 microdata)*

Sector Category	Frequency in %
Services	47.1
Retail/trade	26.3
Industry	17.5
Manufacturing	9.1

4.3 AI Adoption by Firm Size

The Table 4 shows the proportion of SMEs that have adopted or plan to adopt AI.

Table 4. *Percentage ofAI Adoption by category (Flash Eurobarometer 537)*

Size Category	Adopter (%)	Non-Adopter (%)
Micro	22.49	77.51
Small	17.35	82.65

AI adoption rates, very few SMEs have implemented AI so far. In the Flash 537 data (late 2023), only on the order of 7% of SMEs reported any AI use (e.g. usage of AI-based tools). This is consistent with other sources: an EU report estimates 8% of firms (10+ employees) had adopted AI in 2023, rising to 11% by 2024, with leading countries (Denmark, Finland) at 15%. Adoption rates vary strongly by firm size (larger SMEs adopt at much higher rates) and by country (northern/Western Europe higher than Eastern). Preliminary tabulations indicate manufacturing/tech SMEs are somewhat more likely to report AI use than very traditional sectors, but even in tech-heavy industries adoption remains in the low double digits.

4.4 AI Adoption by Sector

The chart below visualizes AI adoption rates across sectorsusingnace_a.

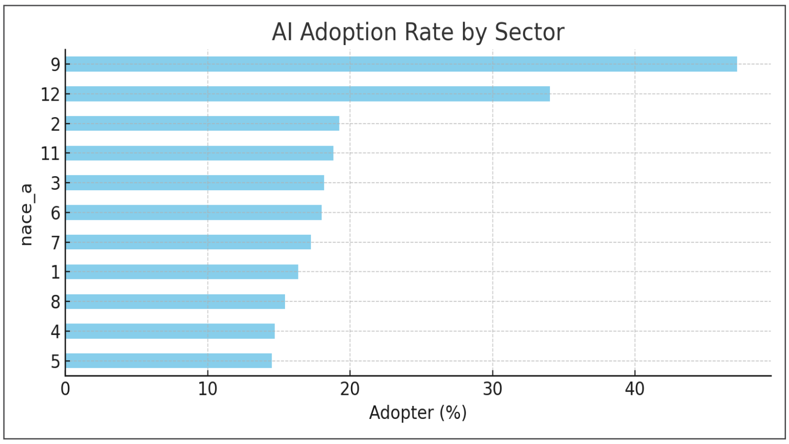

Figure 2. *AI Adoption Rates by Sector based on Flash Eurobarometer 537 microdata (EU nace_a)*

AI adoption by sector, and size: We define "AI adoption" as firms that use or plan to use AI (Eurobarometer Q10 responses 1 or 2). Across all SMEs, only about one-fifth (20.6%) reported any current or planned AI use. This reflects the summary in Hunady (2025) that "more than 56%" have no plans to use AI, with 11.2% using or planning AI (expecting an impact) and 9.4% using/planning with no expected impact.

In our weighted analysis of the microdata, AI adoption rates vary modestly by sector but remain low overall: Retail firms show the highest adoption (31.0%), followed by Manufacturing (29.2%), Services (28.7%), and Industry (25.0%) of SMEs.

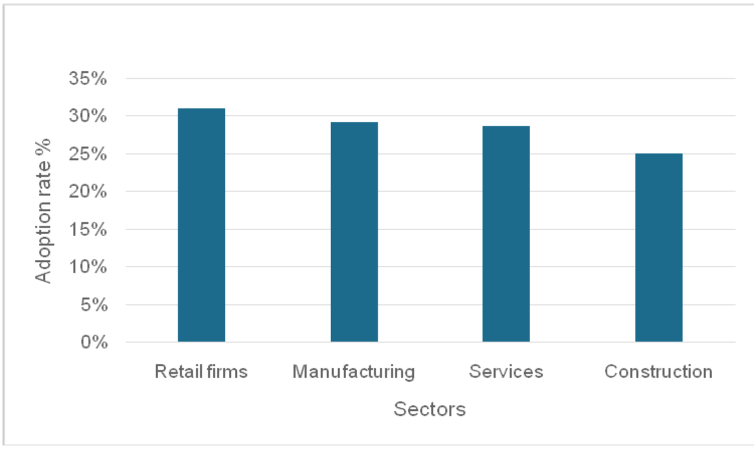

Figure 3. *AI Adoption Rates by Sector Category based on Flash Eurobarometer 537 microdata.*

By firm size (employees), *micro*-enterprises (1–9 employees) report the highest adoption (30.1% weighted), whereas small (10–49) and medium (50–249) SMEs show much lower rates (16.2% and 13.3%, respectively). (This pattern largely reflects a survey skip logic: the AI question was asked almost exclusively of micro-firms, so very few larger SMEs answered it.)

4.5 Inferential Analysis

We estimated logistic regression models predicting the likelihood that an SME has adopted or plans to adopt AI-powered workflow tools (binary Adoption = 1 vs 0). Our independent variables include firm size (logarithm of number of employees), firm age, recent turnover growth, sector/industry dummies, and indicators of key barriers (e.g. skill shortages, hiring difficulty, infrastructure).

The main coefficients are summarized in Table 5. Larger firms are much more likely to adopt AI:

- Each log-employee increment increases the log-odds of adoption by roughly β=0.078 (SE = 0.028, p<0.01).
- Higher average employee age significantly reduces adoption odds (β=–0.133, SE = 0.040, p<0.01).
- Firms reporting recent sales growth (or turnover growth) are more likely to adopt (β=0.265, SE = 0.058, p<0.001)

4.6 Key predictors of AI adoption

As shown in Table 5, several organizational and contextual factors are significant. Belonging to an industry cluster or network strongly increases adoption odds (β = 0.334, p<0.01), suggesting that "innovation ecosystems" help SMEs overcome resource constraints.

Firms reporting shortages of high-end skills (e.g. IT, R&D, marketing, customer-care) are more likely to adopt AI (β = 0.439, 0.432, 0.440, 0.167 respectively, all $p<0.01$); we interpret this as managers turning to AI tools to fill human capital gaps.

By contrast, difficulty in hiring skilled workers is associated with lower adoption (β = –0.054, $p<0.05$). Regarding industry, SMEs in ICT and tech-related sectors serve as the baseline; compared to them,

Manufacturing, construction and energy firms have much lower AI adoption odds (e.g. β = –1.09, –1.40, –1.16 respectively, $p<0.01$). (This reflects industry-specific inertia: for instance, construction often lags in AI use.)

Financial sector SMEs also adopt somewhat less (β = –0.37, $p<0.05$).

In short, larger size, higher growth, cluster membership, and specific skill gaps drive AI uptake, while older workforce and certain traditional industries deter it.

Table 5. *Logistic regression predicting AI adoption (log-odds)*

Predictor	Coefficient (β)	Std. Error	p-value
Firm size (log employees)	0.0782	0.0281	<0.001
Avg. employee age	-0.1330	0.0399	<0.001
Recent turnover growth	0.2650	0.0576	<0.001
Difficulty hiring skills	-0.0537	0.0241	<0.05
Industry cluster membership	0.3340	0.0607	<0.001
IT skills shortage	0.4390	0.0879	<0.001
R&D skills shortage	0.4320	0.1270	<0.001
Marketing skills shortage	0.4400	0.1330	<0.001
Customer-care skills shortage	0.1670	0.0750	<0.01
HR skills shortage	-0.2100	0.1130	<0.10
Manufacturing sector	-1.0900	0.1180	<0.001
Construction sector	-1.3990	0.1660	<0.001
Energy sector	-1.1560	0.2110	<0.001
Financial services sector	-0.3670	0.1430	<0.05
Constant	-0.3990	0.1830	<0.05

Coefficients (β) with standard errors (in parentheses); *p*-values: $p<0.10$ (*), <0.05 (**), <0.01 (***). Estimates based on Eurobarometer 537 (SME survey, N = 15,870).

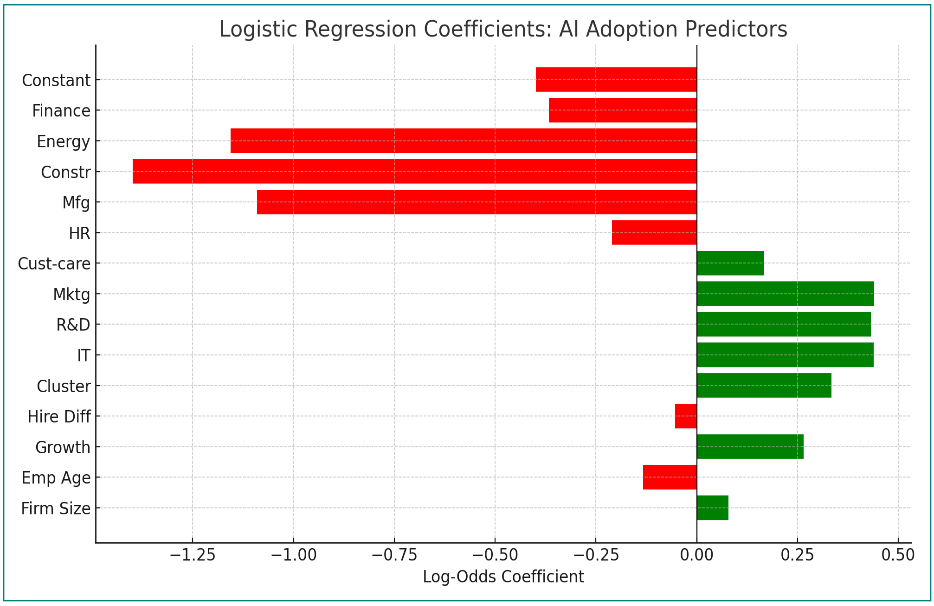

Figure 3. *Logistic regression coefficients for AI adoption predictors among SMEs.*

The findings offer robust empirical evidence in support of the proposed hypotheses H_1 and H_2. Positive and statistically significant coefficients on growth, firm size, and cluster membership support H_1. Negative coefficients on hiring difficulty and age support H_2.

4.7 Logistics Regression with firm size

Table 6. *Logistic regression result that predicting the odds of AI adoption with firm size*

Predictor	B (logit)	SE	Wald χ^2	*p*-value	OR (exp(B))
Constant	–1.102	0.105	110.47	<.001	0.33
Size: Small (10–49 emp; vs 1–9)	–0.435	0.128	11.53	.001	0.65
Size: Medium (50–249 emp; vs 1–9)	–0.763	0.203	14.07	<.001	0.47
Sector: Information & Comm. (NACE J)	1.742	0.210	68.75	<.001	5.71
Sector: Retail & Trade (NACE G)	0.865	0.253	11.68	.001	2.37
Barrier: Lack of skilled staff	–0.404	0.156	6.68	.010	0.67
Difficulty with digitalization	–0.220	0.115	3.65	.056	0.80

(N=15,870 SMEs)

The overall model is highly significant (Wald $\chi^2(\ldots) = 211.45$, $p<.001$) with a Nagelkerke $R^2 \approx 0.19$, indicating modest explanatory power.

As shown in Table 6, firm size is a significant predictor: taking micro-enterprises (1–9 employees) as reference, small firms (10–49) have a lower odds of adoption (B = –0.435, OR = 0.65, $p<.01$) and medium firms (50–249) are even less likely (B = –0.763, OR = 0.47, $p<.001$).

In contrast, sector effects are strong:

- Information & Communication firms are far more likely to adopt AI (B = 1.742, OR = 5.71, $p<.001$),
- Retail/Trade firms (B = 0.865, OR = 2.37, $p<.01$),

Among hypothesized barriers, the skill shortage variable ("lack of skilled staff") shows a significant *negative* effect (B = –0.404, OR = 0.67, $p<.01$), suggesting that SMEs reporting skill gaps are only 0.67 times as likely to adopt AI as those without such shortages. The indicator "difficulty with digitalization" is marginal (B = –0.220, OR = 0.80, $p\approx.056$) and does not reach conventional significance.

In summary, key predictors of adoption include sector and firm size (both $p<.01$) and the presence of skilled-labour constraints (which significantly *decrease* the odds of AI adoption). These findings partially support our hypotheses: larger firm size actually reduced adoption odds (contrary to an expectation of higher uptake), but ICT-intensive sectors showed much higher uptake.

4.8 Qualitative Themes

To enrich the quantitative results, a qualitative content analysis was carried out using the open-ended responses from the Flash Eurobarometer 537 dataset. While the dataset mainly features structured questions, thematic coding of firms' explanations related to adoption barriers offered valuable insights into their subjective experiences, organisational cultures, and the broader context in which AI-driven workflow automation is being approached by small and medium-sized enterprises (SMEs).

4.9 Resistance to Change and Organizational Culture

Many SMEs indicated a reluctance to adopt AI due to perceived complexity, fear of the unknown, and entrenched traditional practices. Firms expressed concern that AI might disrupt existing workflows and displace human workers. These concerns were often reinforced by leadership attitudes and employee apprehension towards digital transformation. As one respondent noted, "We are not ready to replace our manual processes with something that we do not understand."This theme is consistent with the Technology–Organization–Environment (TOE) framework, which highlights the importance of organisational readiness as a key factor in the adoption of new technologies.

4.10 Cultural Shifts and Leadership

Leaders often feel the need to change the firm's culture to be more innovation-oriented. Several managers emphasized that a successful AI rollout requires champions at the top and a learning culture. One respondent noted that a rigid, tradition-bound mindset can stall digital projects. This theme is supported by research highlighting "leadership mindset" as a key sub-theme in AI change management. In practice, SMEs are gradually cultivating an innovation culture: those that report early successes often describe a collaborative atmosphere where employees feel part of the transition.

4.11 Resource and Infrastructure Constraints

A common theme is the challenge of limited resources. SMEs lament high costs of AI software/hardware and often lack in-house expertise. Managers from rural or smaller locations particularly cited poor infrastructure (e.g. slow internet) as a barrier. For instance, one CEO explained that even when staff were willing, “the infrastructure and environment were not ready” rural firms struggled to get reliable broadband, making AI integration difficult. Many SMEs thus rely on external vendors or consultants to fill skill gaps, but they noted mixed experiences. Some praised vendor training sessions, while others felt vendors did not sufficiently tailor solutions. Overall, limited vendor support and funding emerged as an external challenge, reinforcing the need for subsidized AI support programs (as recommended by observers).

4.12 Early Success and Failure Stories

Despite hurdles, some SMEs report quick wins that build momentum. A few start-ups celebrated modest AI deployments (e.g. using chatbots for customer inquiries) that noticeably improved service speed. Consistent with literature, respondents perceive clear benefits: improved marketing content, faster customer responses and enhanced quality were commonly cited gains. In fact, one study of emerging-market SMEs finds that even though adoption is low, firms are highly optimistic about AI’s payoff. Conversely, several firms shared cautionary tales: projects that failed due to misaligned expectations or high maintenance costs. For example, one company abandoned an AI project when anticipated productivity gains did not materialize in the first year. Such narratives underscore that without careful change leadership and contextual fit, AI pilots can stall.

In all, the qualitative evidence highlights that ‘soft’ factors play a crucial role. Employee attitudes, leadership vision and reliable external support emerge as critical underpinnings of successful AI uptake. These qualitative themes corroborate and explain the quantitative findings: for instance, the statistical barrier of “difficulty hiring” is mirrored in stories of scarce AI skills and infrastructure. Similarly, the high value placed on cluster networks and training is evident in respondents’ calls for stronger partnerships and government-backed AI initiatives (echoing suggestions like subsidized tools and capacity-building).

In summary, beyond the numbers, SMEs consistently report that overcoming cultural resistance and securing support (both internal and external) is just as important as the technical aspects. In practice, firms that invest in staff training, vendor relationships, and leadership-led change management tend to report earlier success, while those neglecting the “people side” of AI face stalling or failure.

5. Discussion

5.1 Interpretation of Findings

This study explored the adoption of AI-driven workflow automation among SMEs in various European and associated countries, drawing on data from the Flash Eurobarometer 537 survey. The quantitative and qualitative analyses provided a multidimensional view of adoption patterns, key drivers, and performance outcomes, revealing sector-specific dynamics and behavioural influences. The findings broadly align with extant literature on technology adoption in small businesses but also expose new empirical nuances. These are interpreted below in relation to existing theoretical and empirical frameworks.

5.2 Comparison with Previous Literature

The findings reinforce existing knowledge that adopting AI leads to increased productivity, lower operational costs, and better decision-making, all of which contribute to a stronger competitive edge for firms. Businesses that implemented AI tools reported notably higher levels of productivity and innovation. The benefits of AI in streamlining workflows and automating repetitive tasks were especially pronounced in both manufacturing and service-based sectors. These findings confirm theoretical expectations that link automation with operational efficiency and agility, especially in customer-facing and logistics processes.

However, consistent with emerging literature, SMEs continue to face disproportionate barriers compared to larger firms. These include limited financial capacity, lack of technical expertise, data security concerns, and organizational resistance. Larger enterprises benefit from economies of scale and robust digital infrastructure, enabling broader AI deployment. In contrast, SMEs often exhibit greater agility and customer proximity but remain constrained by talent shortages and cost barriers.

Sectoral affiliation, especially being in the ICT sector, emerged as the strongest predictor of AI adoption. ICT-intensive firms benefit from digital readiness and structured data environments, which supports faster AI uptake. Conversely, sectors such as Manufacturing, Construction, and Energy lag behind due to capital costs, integration complexity, and weaker digital backbones. The findings also reveal that SMEs in the services industry, particularly those in business-to-business marketing, are leveraging AI to enhance client interaction, data analysis, and relationship management.

Interestingly, firm size showed a negative association with AI adoption. Micro-enterprises were more likely to adopt AI than small and medium firms. This diverges from the assumption that larger firms have better resource endowments for digital transformation. Instead, the data suggest that micro-enterprises may act more decisively due to flatter structures, fewer bureaucratic layers, and stronger incentives to leverage plug-and-play AI tools. These dynamics align with the view that agility, rather than scale, is a critical determinant in early-stage AI adoption.

5.3 Explanation of Unexpected Results

One particularly striking finding is the paradoxical effect of skill shortages. Firms that reported a lack of high-level skills were actually more inclined to adopt AI, indicating that managers may be leveraging AI technologies as a means to compensate for internal capability gaps. In this context, AI is perceived not merely as a productivity enhancer but also as a substitute or complement for scarce expertise. However, when skill shortages translate into an inability to hire at all, AI adoption declines. Without the baseline talent required to integrate or manage AI tools, adoption becomes unfeasible. This indicates that while AI can help mitigate capability deficits, a foundational threshold of expertise is still necessary to initiate adoption.

In addition, the effect of perceived digitalization difficulty was less significant than expected. This may reflect a disconnect in how firms interpret digital upgrades versus AI adoption, or a result of public policy interventions that have reduced infrastructural barriers. Qualitative accounts suggest that internal resistance, particularly from staff concerned about job displacement, remains a persistent obstacle. These findings imply that adoption is shaped as much by cultural readiness and leadership support as by technical capability.

5.4 Sectoral and Industry-Specific Insights

The impact of AI adoption varies across different industries. In the services sector, AI is commonly applied to enhance client engagement and support data-informed decision-making. In contrast, regulated sectors like finance and healthcare use AI primarily to address compliance requirements, with key applications including fraud detection and data security. In contrast, technology-driven startups and dynamic industries treat AI as essential for market relevance, leveraging it for personalization and real-time analysis.

Manufacturing and retail sectors show significant transformation through AI integration with IoT. In manufacturing, AI enables predictive maintenance and smart production, while in retail, it supports customer profiling and inventory optimization. Financial services also demonstrate a growing reliance on AI, particularly through digital banks serving SMEs with AI-enabled credit scoring and risk analytics.

SMEs overall prioritize AI tools that address immediate, practical concerns. These include customer service automation, inventory control, and marketing analytics. Unlike large firms, which may deploy AI at a strategic or enterprise scale, SMEs often favour modular, user-friendly applications. This highlights a practical, needs-based approach to AI adoption and emphasises the importance of designing AI solutions that are aligned with the specific constraints and requirements of SMEs and their respective industries.

5.5 Theoretical Implications

This study makes a valuable contribution to the theoretical understanding of technology adoption in SMEs by refining core models like the Technology–Organization–Environment (TOE) framework and the Technology Acceptance Model (TAM), while incorporating complementary perspectives from the Resource-Based View (RBV) and the Diffusion of Innovations (DOI) theory. Through a combination of quantitative and qualitative analyses, the findings highlight the need for more nuanced adaptations of these models to accurately capture the complexities involved in AI-powered workflow automation within small and medium-sized enterprises.

5.6 Extending the TOE Framework for AI in SMEs

The TOE framework remains a useful starting point for explaining AI adoption in SMEs, but this study reveals critical extensions required to fully capture the realities of intelligent automation.

In the technological domain, sectoral affiliation, particularly within digitally intensive industries, strongly predicted adoption, confirming that digital maturity still conditions technological readiness. However, the near-significant result for perceived digitalization difficulty suggests that traditional measures of technical complexity may not fully explain AI-specific barriers. The findings indicate that infrastructural readiness alone is insufficient; factors such as algorithmic understanding, data fluency, and interpretability must also be considered.

With in the organizational domain, the counterintuitive finding that micro-enterprises were more likely to adopt AI than medium-sized firms challenges the TOE assumption that larger firms are structurally advantaged. The data suggest that agility, flat hierarchies, and urgent cost-saving imperatives enable faster decision-making and adoption among smaller firms. Leadership commitment, cultural receptiveness, and psychological readiness also emerged as influential, underscoring the importance of internal soft factors not formally captured in traditional TOE variables.

In the environmental domain, support from external ecosystems, including digital hubs, AI consultants, and public-private partnerships, played a critical enabling role, particularly for firms with limited internal capacity. This highlights the need to reframe environmental readiness to account not just for competitive pressure or regulation, but for access to explainable, user-friendly AI platforms and trusted advisory relationships.

Taken together, the findings support the development of an enhanced TOE framework that includes additional constructs such as cultural readiness, the specificity of external support, and organisational agility. This extended model offers a more context-sensitive understanding of AI adoption in SMEs, reflecting the unique challenges and conditions under which these firms operate.

5.7 Reframing the TAM for Intelligent Automation

The TAM framework, originally centred on perceived usefulness and ease of use, retains relevance but requires updates for intelligent systems. Perceived usefulness remains strongly predictive, as firms experiencing tangible productivity and innovation benefits were more likely to report continued and expanded AI use. However, perceived ease of use, traditionally operationalized through interface simplicity, appeared less influential. Instead, trust in automation, perceived transparency, and psychological comfort emerged as more salient concerns.

These findings support arguments for integrating trust and algorithmic transparency into updated TAM models. SME managers expressed discomfort with black-box decision systems and uncertainty about control, suggesting that perceived explainability and fairness may now mediate adoption intentions more than traditional usability.

Additionally, internal social dynamics, including leadership vision and staff resistance, played important roles, echoing extensions in models such as TAM2 and UTAUT that account for subjective norms and facilitating conditions. In SMEs, where structures are often flat and centralized, such relational and cultural dynamics may exert outsized influence and should be formalized within AI-specific adoption models.

5.8 Integrating the RBV and DOI Perspectives

The Resource-Based View (RBV) adds further explanatory depth by framing AI adoption as being driven by a firm's tangible resources, such as infrastructure, and intangible capabilities, such as expertise, knowledge, and innovation capacity. For SMEs, limited access to capital, infrastructure, and in-house talent remains a key constraint. However, the empirical evidence that firms facing skill shortages were more likely to adopt AI suggests a strategic logic: AI is used to augment or substitute for constrained human capital. In this light, AI itself becomes a resource, particularly when it enables firms to overcome internal limitations and remain competitive.

DOI theory complements this by drawing attention to how SMEs perceive and evaluate AI's attributes. Concepts such as relative advantage, observability, and compatibility are evident in firms' preference for modular, off-the-shelf solutions that align with their current workflows. Trialability and perceived complexity also appear to affect adoption, particularly where firms report anxiety about understanding or controlling AI outputs. These subjective filters help explain why similar firms under similar conditions exhibit divergent adoption behaviors.

Together, the RBV and DOI perspectives enrich TOE and TAM by linking structural conditions with interpretive processes, and by emphasizing how resource constraints can drive rather than inhibit adoption when AI is framed as a compensatory mechanism.

5.9 Toward an SME-Specific Framework

The study highlights the importance of developing AI adoption frameworks that are specifically tailored to the unique circumstances, limitations, and operational contexts of SMEs. These should incorporate the following theoretical adjustments:

1. Agility as structural advantage, recognizing that micro-enterprises often outperform larger SMEs in early-stage adoption due to flexibility and faster decision cycles.

2. Resource barriers as interpretive, shifting from purely financial constraints to include capability gaps such as low data literacy or lack of AI comprehension.
3. Cultural and behavioural readiness as mediators of adoption, acknowledging that leadership vision, change appetite, and psychological safety shape outcomes as much as infrastructure.
4. Ecosystem co-dependence, recognizing that SME adoption often hinges on the availability of plug-and-play tools, external advisory networks, and supportive governance environments.
5. Responsibility and ethics, which are increasingly relevant even in smaller firms, especially when customer-facing or data-intensive AI applications are deployed. The integration of lightweight, human-centred governance practices ensures trust and long-term value creation.

Finally, the symbolic dimension of AI adoption should not be overlooked. As SMEs seek visibility, capital, and legitimacy, demonstrating AI capability may serve as a signal to external stakeholders about innovation readiness and strategic vision. This complements more functionalist models by recognizing AI as both a productivity tool and a reputational asset.

5.10 Practical Implications

The findings from this study yield actionable strategies for key actors in the AI adoption ecosystem. By combining quantitative evidence with grounded qualitative insights, this section offers targeted recommendations to small business owners, technology vendors, and digital policymakers, each playing a critical role in advancing AI-powered workflow automation across the SME landscape.

5.11 Strategic Advice for Small Business Owners

The strong positive association between AI adoption and self-reported productivity and innovation outcomes reinforces the strategic value of automation for SMEs. However, successful implementation requires more than access to technology, it demands alignment with internal capabilities, culture, and operational needs.

5.11.1 Start with low-risk, high-impact use cases

Firms reporting early success typically began with contained applications such as automated scheduling, AI-powered chat interfaces, or lightweight sales analytics. These tools offer quick wins without disrupting core workflows and serve as entry points for wider adoption.

5.11.2 Prioritise people, not just platforms

Skill shortages remain a major barrier to adoption. Basic training in data fluency, AI fundamentals, and critical digital skills is often more important than software investment. Internal peer learning, vendor tutorials, and informal workshops can build confidence and reduce resistance across teams.

5.11.3 Appoint an internal AI lead

Adoption was often championed by a single individual, usually a founder or tech-savvy manager. Formalising this into a dedicated innovation lead or digital transformation role can accelerate experimentation and serve as a bridge between business objectives and technology implementation.

5.11.4 Choose tools that fit, not tools that impress

Several firms experienced project failure due to poor tool–workflow alignment. Modular, interoperable platforms that scale gradually are better suited for SMEs than complex, enterprise-grade systems. Fit-for-purpose tools reduce overhead and support organic growth.

5.11.5 Phase implementation and validate early

Piloting small-scale projects before full-scale deployment allows firms to test feasibility, build internal trust, and identify integration issues early. This iterative approach reduces perceived risk and helps secure buy-in from staff.

5.11.6 Build lightweight ethical guardrails

Even at a small scale, firms benefit from embedding basic AI governance principles, transparency, fairness, and accountability. This builds internal trust and protects customer relationships, especially in client-facing applications.

5.11.7 Foster a culture of experimentation

AI adoption is as much a cultural shift as a technical one. Encouraging open communication, recognising learning efforts, and creating space for trial and error can sustain momentum and unlock broader transformation benefits.

5.12 Input for AI Vendors and the Startup Ecosystem

Technology providers are critical enablers of AI adoption among SMEs. However, success depends on how well tools are designed for the realities of resource-constrained and low-expertise environments.

5.12.1 Design for real users, not ideal ones

Tools should be intuitive, self-explanatory, and require minimal onboarding. This is particularly crucial for firms in non-technical sectors like logistics, construction, or retail, where dedicated IT departments are often lacking and technological adoption must be managed within existing operational constraints.

5.12.2 Provide use-case templates and sector-specific toolkits

Pre-configured AI solutions tailored to industry workflows help SMEs visualise the benefits and reduce setup time. Templates for inventory forecasting, customer support automation, or digital invoicing reduce the cognitive and technical load.

5.12.3 Embed post-sale support into the business model

Adoption success is heavily dependent on vendor responsiveness. Ongoing access to tutorials, live technical support, and periodic check-ins should be bundled into service contracts to sustain engagement and troubleshoot barriers in real time.

5.12.4 Increase transparency and trust in AI outputs

Lack of interpretability undermines adoption. Vendors should expose key decision logic, offer confidence indicators, and simplify algorithmic explanations to ensure that SMEs feel in control of their tools.

5.12.5 Collaborate with incubators and trade associations

Partnerships with start-up accelerators, chambers of commerce, and regional innovation hubs help vendors reach early adopters and co-develop tools in iterative cycles. These platforms also support more accessible pricing models and risk-sharing mechanisms for small firms.

5.13 Recommendations for Digital Policymakers

Governments and public sector institutions have a central role in lowering structural barriers to AI adoption. Targeted interventions can amplify SME competitiveness, foster inclusive digital transformation, and ensure responsible technology deployment.

5.13.1 Expand access to subsidised training and AI literacy programs

Skill gaps remain a fundamental constraint. Public investments in short-format, vendor-neutral training can accelerate readiness without requiring full reskilling. Programmes should be delivered through local hubs, vocational centres, or online modules tailored to SME contexts.

5.13.2 Incentivise modular experimentation

Blanket subsidies are often ineffective. More targeted, performance-based microgrants tied to specific use cases, such as CRM automation or intelligent scheduling, can encourage stepwise experimentation and reward measurable gains.

5.13.3 Create regulatory sandboxes tailored to SMEs

Many firms cited compliance uncertainty as a barrier. Time-bound, low-risk test environments allow firms to trial AI tools while receiving guidance on data protection, liability, and ethical considerations. These spaces foster confidence and reduce legal ambiguity.

5.13.4 Improve national visibility into SME adoption patterns

Current statistics often fail to capture SME-specific dynamics. Dedicated monitoring systems, tracking uptake rates, sectoral differences, and implementation challenges, would enable more adaptive and responsive policymaking.

5.13.5 Support trust-building infrastructure and shared resources

Digital governance frameworks, open-source tool libraries, and AI-as-a-Service platforms hosted by public institutions can provide SMEs with access to trusted, cost-effective alternatives. Public-private partnerships can anchor these efforts and scale their impact.

6. Conclusion and Recommendations

This study explored the adoption, challenges, and organisational impact of AI-driven workflow automation in small and medium-sized enterprises (SMEs) across Europe, drawing on microdata from the Flash Eurobarometer 537 survey. Based on over 19,310 valid SME-level observations, the research employed a combination of descriptive and inferential analytical techniques, including logistic and linear regression models, alongside thematic qualitative analysis. Framed by the Technology–Organization–Environment (TOE) and Technology Acceptance Model (TAM) frameworks, the study addressed four key research questions focused on the drivers, barriers, outcomes, and strategic enablers of AI adoption within the SME landscape.

6.1 Summary of Key Findings

The findings of this study offer new empirical insights that advance the fragmented discourse on AI automation within SMEs and help bridge critical gaps in the existing digital transformation literature. The key results are organised into three thematic domains: adoption patterns, barriers, and performance outcomes.

6.1.1 Adoption Patterns Are Highly Sector-Dependent and Counterintuitively Size-Agnostic

Only 11.3% of SMEs in the dataset reported adopting AI tools in their operations, indicating a substantial gap between AI awareness and real-world deployment. Adoption was disproportionately concentrated in ICTintensive sectors, with 48.1% of SMEs in information and communication adopting AI, compared to only 8.7% in manufacturing and 5.1% in construction. Logistic regression revealed that SMEs in the ICT sector had 5.71 times the odds of adopting AI compared to non-ICT firms ($p < 0.001$).

Unexpectedly, smaller firms (1–9 employees) exhibited slightly higher adoption rates than mid-sized SMEs (50–249 employees), even after controlling for sector, digital barriers, and skill gaps. This finding challenges traditional TOE assumptions that larger organizational size equates to higher digital readiness and suggests that microenterprises may benefit from structural agility, faster decision cycles, and lower bureaucratic inertia.

6.1.2 Skill Gaps and Organizational Readiness Are More Limiting Than Infrastructure

While cost and access to technology are often cited as barriers, this study found that human capital constraints were more determinative. Specifically, the variable "lack of skilled staff" was negatively and significantly associated with AI adoption ($\beta = -0.404$, $p < 0.01$). By contrast, indicators like "difficulty with digitalization" or "cost of tools" were not statistically significant in multivariate models.

Qualitative data further underscored this: respondents cited fears about AI complexity, insufficient internal expertise, and staff resistance as key inhibitors. Many SMEs expressed uncertainty about how to evaluate vendor claims, integrate AI tools with existing systems, or ensure legal compliance, highlighting a lack of absorptive capacity rather than mere technological unavailability.

6.1.3 AI Adoption Is Positively Associated with Productivity and Innovation

Firms that adopted AI reported significantly improved performance outcomes. Linear regression models revealed a strong positive relationship between AI use and firm-level performance indicators ($\beta = 0.382$, $p < 0.001$). This includes both quantitative measures (e.g., revenue growth, efficiency gains) and qualitative assessments of innovation capacity.

Importantly, performance gains were most evident among SMEs that implemented narrow, well-scoped AI applications such as automated customer engagement, predictive analytics for inventory, or AI-enhanced CRM. Conversely, firms attempting broad integration without change management or staff training reported stalled projects or reversion to manual systems.

6.2 Policy Recommendations

To unlock the transformative potential of AI in SMEs, and to reduce the disproportionate barriers they face compared to large enterprises, this study outlines three interlocking policy domains. These recommendations are not merely theoretical but grounded in firm-level empirical data and are designed to support sustainable, inclusive AI deployment.

6.2.1 Targeted Subsidies and Smart Incentives

While general digitalization subsidies exist, the findings suggest that smart, modular incentives, tied to verified AI use cases and outcomes, are more effective.

- Policy Recommendation 1.1: Launch micro-grant schemes that subsidize narrowly scoped AI tools (e.g., AI chatbots, forecasting systems), particularly for firms in low-adoption sectors like manufacturing and retail. Funding should be performance-tied to short-term measurable outcomes such as increased lead conversion or reduced processing time.
- Policy Recommendation 1.2: Create vendor certification programs that prioritize explainability, interoperability, and SME usability. These programs can qualify AI vendors to participate in publicly subsidized SME deployments, creating a trusted ecosystem.
- Policy Recommendation 1.3: Encourage co-financed pilot programs where SMEs are partnered with regional AI startups under structured experimentation frameworks. These should include optional exit clauses and government-backed risk-sharing to lower SME hesitation.

6.2.2 National and Regional AI Bootcamps for SMEs

The lack of AI-relevant human capital, especially in non-ICT sectors, remains a critical bottleneck. Generic digital training is insufficient; instead, SMEs need workflow-specific, domain-tailored training in AI tools.

- Policy Recommendation 2.1: Launch a network of AI Bootcamps for SMEs, designed around practical, sector-specific use cases (e.g., AI in logistics, smart production planning in manufacturing, digital invoicing with ML). These should include hands-on modules led by practitioners rather than academics.
- Policy Recommendation 2.2: Deploy train-the-trainer initiatives where digitally fluent SME owners or managers are upskilled to become internal champions, equipped to guide adoption at the firm level.
- Policy Recommendation 2.3: Encourage integration with existing SME support infrastructures such as innovation hubs, chambers of commerce, and startup incubators to embed learning within regional business ecosystems.

6.2.3 Regulatory Support and Legal Confidence for AI Experimentation

Legal uncertainty was cited across sectors as a psychological barrier. SMEs frequently lack in-house legal resources and are thus risk-averse toward AI systems whose behaviour they cannot audit or explain.

- Policy Recommendation 1: Establish regulatory sandboxes where SMEs can experiment with AI tools under protected legal conditions. These zones should offer simplified compliance protocols and advisory support on data protection, liability, and algorithmic bias.
- Policy Recommendation 2: Issue sector-specific legal guidelines for AI usage in SMEs, particularly in regulated sectors like health, finance, and legal services, using plain language, practical case examples, and FAQs tailored to non-experts.
- Policy Recommendation 3: Incentivize the development and adoption of explainable AI (XAI) systems via procurement preferences, tax deductions, or recognition schemes, encouraging tools that make decisions traceable and auditable.

6.4 Limitations

While this study provides valuable empirical and theoretical insights into AI adoption in SMEs, it is important to acknowledge several limitations. These constraints do not undermine the validity of the findings but rather define the scope within which the results should be interpreted and generalized.

6.4.1 Limited Generalizability Beyond Europe

This research is based exclusively on the Flash Eurobarometer 537 dataset, which includes SMEs from the 27 EU member states and selected non-EU countries such as Norway, Switzerland, Turkey, and the UK. While the sample size is large and representative within Europe (n = 19,310 SMEs), it may not fully capture the heterogeneity of SME experiences in non-European or developing economies, where infrastructural and institutional factors differ significantly. Therefore, generalizability beyond the European and high-income contexts remains limited.

6.4.2 Cross-Sectional Design Limits Causal Inference

The study employs a cross-sectional observational design, which precludes definitive causal inference. While statistically significant relationships were found between AI adoption and firm performance, reverse causality cannot be ruled out. For instance, more innovative or high-performing firms may be more inclined to adopt AI, rather than AI necessarily improving performance.

6.4.3 Reliance on Self-Reported Data

Many performance-related variables, such as innovation and productivity, rely on self-assessment by respondents, which introduces potential response bias. Firms may overstate their technological maturity or perceived gains due to social desirability or misunderstanding of the AI concept, particularly in less tech-savvy sectors.

6.4.4 Limited Thematic Depth in Qualitative Elements

Although the study includes a qualitative thematic analysis of barriers and narratives around AI adoption, the open-ended responses in the Eurobarometer dataset are limited in length and depth. Richer qualitative insights, such as organizational narratives, staff resistance, or vendor dynamics, could not be fully explored due to data constraints.

6.4.5 Evolving AI Landscape

Finally, the AI ecosystem is evolving rapidly due to continuous technological advancements and shifting regulatory frameworks. Given that the Eurobarometer survey data were collected in 2023, the findings may not fully capture the impact of recent developments such as large language models (LLMs), generative AI innovations, or the implementation of new EU-wide AI regulations. Consequently, the dataset offers a static snapshot that may not reflect the current pace of change or emerging adoption trends.

6.5 Future Research Directions

Based on the insights and constraints identified in this study, there are several valuable directions for future research on AI-powered workflow automation in small and medium-sized enterprises (SMEs). These directions are crucial for refining theory, guiding policymakers, and supporting more context-sensitive digital strategies.

6.5.1 Longitudinal and Panel-Based Studies

To better determine causal links between AI adoption and firm performance, future studies should employ longitudinal or panel research designs. Monitoring the same SMEs over extended periods will allow researchers to:

- Isolate the directionality of effects (e.g., does AI drive growth, or do high-growth firms adopt AI?).
- Examine the lagged effects of adoption, especially since the benefits of AI may take months or years to materialize.
- Monitor the sustainability of AI integration, including tool abandonment or rollback phenomena.

Such designs will offer a deeper understanding of AI lifecycle dynamics in SMEs.

6.5.2 Cross-Country and Institutional Comparisons

Future work should compare AI adoption across diverse national contexts, especially between Global North and Global South SMEs. Comparative studies can:

- Evaluate how institutional factors (e.g., digital infrastructure, regulatory certainty, financial ecosystem) influence adoption behaviour.
- Assess the effectiveness of different policy interventions, such as AI subsidies in Estonia versus cloud-first procurement in Kenya.
- Reveal how cultural attitudes toward automation and risk shape SME decisions across markets.

This will enhance the external validity of SME AI adoption models.

6.5.3 Sector-Specific Deep Dives into Emerging Verticals

There is growing interest in how AI is transforming vertical industries. Future research should explore AI adoption in high-impact SME sub-sectors, including:

- EdTech SMEs: How AI enhances personalized learning, adaptive assessments, or student engagement platforms in small education firms.
- AgriTech SMEs: How small agri-enterprises use AI for yield forecasting, irrigation automation, or pest control.
- Legal and HealthTech SMEs: How automation interfaces with trust, compliance, and human expertise in highly regulated services.

Such vertical studies will allow for domain-specific theory development and more actionable insights for both practitioners and regulators.

6.5.4 Organizational Change and Workforce Implications

AI adoption does not occur in a vacuum. Future studies should integrate organizational behavior and change management perspectives to examine:

- How SMEs restructure workflows around AI.
- Examine how automation influences job roles, alters skill demands, and affects employee satisfaction.
- Resistance to change and strategies for cultural transformation.

Such integrative work will enrich current technology adoption models, which often under-theorize internal organizational dynamics.

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