The Factors Influencing the Adoption of AI in E-Commerce by SMEs in Shandong Province

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ABSTRACT

This study delves into the factors influencing the adoption of Artificial Intelligence (AI) in e-commerce by small and medium-sized enterprises (SMEs) in Shandong Province, China. Leveraging a quantitative approach with a 300-questionnaire survey among 305 SMEs, it uncovers that technological, organizational, and environmental factors play crucial roles. Technological factors, such as perceived ease of use and usefulness, exert the strongest influence on SMEs' attitude towards AI adoption. Adequate financial resources, skilled personnel, and top management support within organizations enhance the likelihood of AI adoption. External pressures like competition and customer demand also drive SMEs to consider AI. However, SMEs face challenges, including high costs and skills shortages, despite a generally positive attitude towards AI. The research findings offer practical implications for SMEs, policymakers, and industry stakeholders. SMEs can integrate user-friendly AI solutions, explore cost-effective options like AI-as-a-Service (AIaaS), and seek government financial incentives. Policymakers can enhance financial incentives, collaborate with educational institutions to address skills shortages, and streamline data regulations. Industry stakeholders, such as technology providers and industry associations, can develop more suitable AI solutions and promote best practices and industry standards. Future research should focus on long-term impact studies, the influence of emerging technologies like generative AI, improvement of data collection methodologies, and in-depth exploration of factor interactions to further understand and promote AI adoption in Shandong's e- commerce SMEs.

Keywords: Artificial Intelligence (AI), Small and Medium-Sized Enterprises (SMEs), Technological Factors, Organizational Factors, Environmental Factors.

INTRODUCTION

Background of the Study

In the era of rapid global digital advancement, the integration of artificial intelligence (AI) and e-commerce is reshaping business ecosystems. In China, small and medium-sized enterprises (SMEs), particularly in Shandong Province, where they account for 92% of all enterprises stand at a pivotal moment for digital transformation. Their ability to adopt AI not only enhances competitiveness but also contributes to regional industrial upgrading and high-quality economic development. Understanding the factors influencing AI adoption among Shandong's SMEs in e-commerce holds both theoretical and practical significance.

Globally, AI-driven innovations are transforming e-commerce from traditional to intelligent models. According to Statista (2023), global e-commerce transaction volume is expected to grow from $4.9 trillion in 2021 to $7.4 trillion by 2025. Core technologies like intelligent recommendation systems, supply chain optimization, and dynamic pricing engines are central to this shift (Huang & Rust, 2021). In China, the "Digital China" initiative has accelerated digital transformation across provinces, with Shandong leveraging its “Digital Shandong” blueprint to integrate AI in e-commerce through infrastructure investment, policy support, and industry ecosystem cultivation. However, for SMEs with limited resources, adopting AI is a complex endeavor. Challenges such as technological sophistication, financial limitations, talent shortages, and data governance pose significant barriers (Gartner, 2020; Venkatesh et al., 2012). Despite these obstacles, growing consumer expectations and competitive pressures compel SMEs to pursue technological upgrades. For example, a

Shandong-based clothing retailer saw a 20% increase in online sales within six months by implementing an AI recommendation engine (Li & Zhang, 2022), highlighting the value of AI in boosting efficiency and customer experience.

Amid China's broader digital economic shift, Shandong's SMEs are undergoing strategic restructuring. Their potential to realize intelligent transformation through AI presents an essential opportunity for industrial evolution. This study adopts the Technology-Organization-Environment (TOE) framework to analyze the key drivers influencing AI adoption, focusing on technology diffusion, organizational resources, and institutional support. The aim is to construct an integrated model offering theoretical insights and actionable strategies for Shandong's e-commerce modernization.

AI's role in value creation is increasingly evident. It enhances customer experience through personalized recommendations, improves supply chain efficiency via intelligent decision systems, and supports precision marketing through dynamic pricing (Chui et al., 2018). These tools help SMEs overcome traditional resource constraints and build digital agility (Laudon & Traver, 2021). In Shandong, SMEs face urgent pressure to transform digitally due to technological shifts and intensifying market competition. Strategic AI deployment ranging from automation to intelligent analytics is essential for closing innovation gaps (Chen et al., 2022).

From a technology adoption standpoint, perceived usefulness and ease of use are critical cognitive factors (Davis, 1989). SMEs' belief in AI's ability to optimize operations and enhance customer value influences their investment decisions. Innovation diffusion theory highlights technology compatibility and integration costs as key barriers (Rogers, 2003). Organizational readiness comprising technological assets, financial capacity, and leadership commitment also shapes the effectiveness of AI adoption (Tornatzky & Fleischer, 1990). In SMEs, where decision-making is centralized, leadership initiative plays a decisive role in overcoming adoption challenges (Lumpkin & Dess, 1996).

Environmental pressures including competition, evolving consumer expectations, and regulatory compliance further motivate AI adoption (Zhu et al., 2006). Shandong's local government has facilitated this process through tax incentives, incubators, and talent programs under the "Digital Shandong" initiative. These efforts reduce innovation uncertainty, lower adoption costs, and foster institutional support for AI diffusion. Despite these supports, adoption remains difficult due to high entry costs in technology, workforce training, and infrastructure maintenance (Gartner, 2020). A shortage of skilled AI professionals hinders full integration, while regulatory compliance and data governance obligations add complexity (European Commission, 2020). Psychological resistance and fear of job displacement also contribute to internal friction (Venkatesh et al., 2012).

National policies like "Made in China 2025" support innovation in key sectors, including e-commerce (State Council, 2015). Local initiatives in Shandong have further promoted AI adoption through financial and technical support (Shandong Provincial Government, 2021). Success stories such as an apparel retailer increasing sales through AI and a catering SME optimizing its supply chain (Li & Zhang, 2022; Wang, 2021) demonstrate the transformative potential of AI for regional SMEs.

Problem Statement

The integration of artificial intelligence (AI) into e-commerce is vital for enhancing customer experience, optimizing operational efficiency, and refining marketing strategies. Yet, there is a lack of research on how small and medium-sized enterprises (SMEs), particularly in regional contexts like Shandong Province, China, are adopting AI. This project focuses on SMEs in Shandong, addressing specific challenges they encounter and filling a notable gap in current literature. AI's rapid development offers enterprises unique opportunities to boost competitiveness and contribute to economic growth. However, for SMEs in Shandong, these opportunities remain underutilized due to distinct challenges such as limited financial resources, insufficient technical expertise, data privacy concerns, and resistance to change (EU, 2020; Venkatesh et al., 2012). These barriers must be acknowledged to develop strategies tailored to the regional SME landscape.

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One of the most critical barriers is the high upfront investment needed for AI technologies. For small firms operating with tight budgets and restricted access to external financing, the costs of acquiring AI tools, training staff, and maintaining systems are prohibitive (Gartner, 2020). This financial burden makes it difficult for many SMEs to invest in the necessary infrastructure and technologies for effective AI integration. In addition to funding issues, the scarcity of skilled personnel further impedes AI adoption. Specialized knowledge is essential for implementing AI solutions, yet many SMEs in regional settings lack access to qualified professionals and technical training opportunities. In Shandong Province, these skills gap significantly hinders AI deployment.

Data privacy and security also present substantial obstacles. AI-enhanced e-commerce operations require large volumes of consumer data, demanding strict data governance practices. However, many SMEs lack the resources and expertise to enforce proper data protection measures, leading to risks of data breaches and non-compliance (EU, 2020). To support technological advancement, national and regional governments have introduced initiatives. For example, the “Made in China 2025” policy promotes innovation in key sectors such as e-commerce (State Council of the People's Republic of China, 2015). Complementarily, the Shandong provincial government offers financial incentives, training programs, and technical assistance to SMEs integrating AI (Shandong Provincial Government, 2021).

There are success stories. A local apparel retailer in Shandong reported a 20% increase in online sales after implementing an AI-powered recommendation engine (Li & Zhang, 2022). Similarly, SMEs in the food and beverage sector have applied AI-based inventory systems to reduce stockouts and improve supply chain efficiency (Wang, 2021). These cases demonstrate AI’s potential and provide practical insights, yet most prior studies focus on large firms or developed economies, neglecting regional SMEs (Chui et al., 2018; Huang & Rust, 2021).

A critical gap in the literature is the limited understanding of region-specific and industry-specific factors that influence AI adoption. Shandong’s SME sector is diverse and vital to the province’s economic growth (Chen et al., 2022), but few studies have explored how local conditions shape AI integration. Another underexplored area is organizational readiness. While factors like financial strength, technological infrastructure, and employee skill levels are acknowledged as influential (Tornatzky & Fleischer, 1990), they are often examined in the context of larger firms. SMEs in Shandong may face compounded constraints, but research on practical interventions remains scarce.

External factors such as market competition and customer demand also influence AI adoption, but the extent of their impact on SMEs in Shandong is unclear (Zhu et al., 2006). Moreover, there is little analysis on how SMEs perceive the need for personalized services through AI. Although research has identified barriers such as high costs, data security, and organizational inertia (Gartner, 2020; European Commission, 2020; Venkatesh et al., 2012), how these manifest specifically in Shandong SMEs remains undocumented. Entrepreneurial orientation, which could affect adoption decisions, is also largely overlooked (Lumpkin & Dess, 1996).

Without an integrated framework that addresses technological, organizational, and environmental dimensions, current research lacks a holistic view. This study aims to fill that void by investigating the specific factors affecting AI adoption among SMEs in Shandong Province. In doing so, it seeks to provide actionable insights for policymakers, practitioners, and future research, contributing to the sustainable development of China's digital economy.

Research Objectives

RO1: To identify the technological factors that influence the AI adoption in e-commerce by SMEs in Shandong Province.

RO2: To examine the organizational factors that influence the AI adoption in e-commerce by SMEs in Shandong Province.

RO3: To access the environmental factors that influence the AI adoption in e-commerce by SMEs in Shandong Province.

Research Questions

RQ1: Do technological factors influencing the AI adoption in e-commerce by SMEs in Shandong Province?

RQ2: Do organizational factors influencing the AI adoption in e-commerce by SMEs in Shandong Province?

RQ3: Do environmental factors influencing the AI adoption in e-commerce by SMEs in Shandong Province?

Research Hypotheses

H1: Technological factors are positively related to the likelihood of SMEs in Shandong Province adopting AI in e-commerce.

H2: Organizational factors are positively related to the likelihood of SMEs in Shandong Province adopting AI in e-commerce.

H3: Environmental factors are positively related to the likelihood of SMEs in Shandong Province adopting AI in e-commerce.

Scope and Limitations

The present project focuses on SMEs in Shandong Province, China, and examines their impact on AI adoption. By focusing on this specific region, the research can explore the local context in depth. Shandong has its own set of government policies promoting digital transformation, including specific incentives and support programs for AI adoption. These regional initiatives can be closely examined, and their impact on SMEs' AI adoption decisions can be accurately analyzed. The diverse industrial composition of Shandong, including manufacturing, agriculture, and service- related SMEs, also provides a rich backdrop for understanding how different sectors approach AI implementation in e-commerce.

Despite its narrowed focus, the present research is not without its limitations. Firstly, the results may not be generalizable to SMEs in other parts of China or globally, due to the fact that the economic development levels and technological infrastructure vary greatly between Shandong and other provinces, such as Guizhou or Zhejiang. Secondly, SMEs in more economically advanced regions may have greater access to capital for AI adoption, while those in less developed areas might face even more severe resource constraints. In addition, while Shandong boasts a diverse range of industries, it is possible that certain niche or emerging sectors may be underrepresented. Consequently, start-ups in the fintech or high-tech innovation-driven e-commerce segments in Shandong may have different AI adoption experiences compared to traditional manufacturing-based SMEs.

The process of data collection is also accompanied by several challenges. The risk of selection bias is present if the sample of SMEs studied is not truly representative. For example, if the survey is mainly targeted towards larger SMEs or those located in certain urban areas, the findings may not be representative of the experiences of smaller, rural-based SMEs. By the time the research is completed, new advancements in AI, such as more sophisticated machine-learning algorithms or technologies designed to enhance privacy, may have emerged, potentially altering the factors influencing AI adoption.

The Significant of Study

This study holds significant theoretical and practical implications for understanding AI adoption in e-commerce among SMEs, particularly in regional contexts like Shandong Province. Theoretically, it addresses the existing research gap by providing empirical insights into the unique technological, organizational, and environmental factors influencing AI adoption in a specific regional economy. While global studies often focus on large enterprises or developed economies, this research deepens the understanding of how SMEs in a developing regional context navigate AI implementation. By integrating the Technology Acceptance Model (TAM) and Diffusion of Innovation Theory, the study extends these frameworks to evaluate their applicability in Shandong’s SME ecosystem, where organizational agility and policy support play distinct roles. For instance, the finding that technological factors (such as perceived ease of use and compatibility) exert the strongest influence on adoption attitudes enriches TAM by highlighting regional nuances in technology perception. Additionally, the study's focus on the interplay between government policies (such as "Digital Shandong" initiatives) and SME adoption behavior contributes to the literature on institutional support for technological diffusion in emerging markets.

Practically, the research offers actionable insights for multiple stakeholders. For SMEs, the identification of cost-effective strategies like AI-as-a-Service (AIaaS) and the importance of top-management support provides a roadmap for overcoming financial and skill-related barriers. Policymakers can leverage the findings to refine incentives, such as enhancing tax breaks for AI adoption or collaborating with educational institutions to address talent shortages, as evidenced by the study's emphasis on skills gaps. Industry stakeholders, including technology providers and associations, can develop tailored solutions that align with SMEs' operational realities, such as user- friendly AI tools compatible with existing e-commerce platforms. Moreover, the study's emphasis on customer demand and competitive pressure as external drivers underscores the need for SMEs to prioritize AI-driven personalization and operational efficiency to maintain market relevance.

This research contributes to China's broader digital transformation agenda by showcasing how regional SMEs can leverage AI to enhance competitiveness, supporting the "Made in China 2025" initiative. By highlighting both the potential and challenges of AI adoption, the study fosters a more nuanced approach to technology policy, emphasizing the need for context-specific interventions rather than one-size- fits-all solutions. As AI continues to reshape global commerce, this work provides a critical foundation for future studies on emerging technologies like generative AI in regional SME ecosystems, advocating for longitudinal research to assess long-term impacts and dynamic factor interactions. Ultimately, the study bridges theoretical frameworks with practical challenges, offering a vital resource for academics, policymakers, and industry leaders committed to advancing AI-driven innovation in SMEs.

LITERATURE REVIEW

AI Adoption in E-commerce

The adoption of artificial intelligence (AI) in e-commerce varies significantly across countries and regions, offering valuable lessons for SMEs in Shandong Province. International experiences illustrate diverse approaches to AI integration, showcasing both the opportunities and challenges that accompany this technological shift.

In the United States, leading e-commerce firms such as Amazon have pioneered the use of AI to enhance customer experiences and drive sales. AI algorithms analyze massive datasets including browsing behaviour, purchase history, and customer segmentation to deliver highly personalized product recommendations (Odeyemi et al., 2024). Even small businesses in the U.S. are leveraging AI through accessible platforms such as Google Cloud and Microsoft Azure. These AI-as-a-service (AIaaS) tools offer pre-trained models for natural language processing, image recognition, and recommendation systems that can be integrated into e-commerce websites and mobile apps, reducing the need for large internal R&D investments (Gupta et al., 2023).

In Europe, data security regulations present both obstacles and opportunities for AI adoption. The emphasis on user privacy requires e-commerce businesses to be transparent and secure in their data practices. This can be resource-intensive for SMEs but also pushes innovation in privacy-focused AI. For example, some European SMEs have begun employing differential privacy techniques, which protect individual user identities while still allowing meaningful data analysis (Zhu et al., 2020). In Asia, countries such as South Korea and Japan have leveraged their advanced technological infrastructure to implement AI in unique and user-centric ways. In South Korea, AI and augmented reality (AR) technologies are being used in virtual fitting rooms, allowing customers to try on clothing digitally. This not only enhances the user experience but also reduces return rates (Lee et al., 2020). In Japan, e-commerce firms employ AI-powered chatbots that are culturally and linguistically attuned to Japanese consumer preferences, enabling more accurate and personalized customer service (Sartortt et al., 2020).

Emerging economies such as India also offer instructive examples. Indian e-commerce firms are adopting AI to meet the needs of a diverse customer base. Voice-activated shopping assistants have become popular, especially among users with limited digital literacy. Furthermore, AI is improving supply chain efficiency through demand forecasting, route optimization, and inventory management, helping businesses navigate the country's complex logistics landscape (Jain et al., 2020). For SMEs in Shandong Province, these international experiences present actionable insights. U.S. models emphasize the accessibility of cloud-based AI tools, while European firms highlight privacy-conscious innovation. South Korea and Japan offer inspiration for customer-focused applications, and India demonstrates how AI can serve varied consumer segments. Encouragingly, the Shandong Provincial Government has introduced policies to support AI adoption through financial incentives, training programs, and technical assistance (Nayal et al., 2023).

Sector-specific applications within Shandong further illustrate AI's transformative potential. In retail e-commerce, AI-driven demand forecasting enables SMEs to predict seasonal trends by analyzing sales history, market behavior, and local events. For example, a ready-to-wear clothing retailer in Shandong can use predictive models to stock appropriate inventory, minimizing excess while avoiding stockouts—thus improving operational efficiency and customer satisfaction (Agnani et al., 2022).

In the food and beverage sector, AI helps ensure product quality and freshness. Computer vision can detect spoilage or damage in perishable goods, while predictive analytics can optimize inventory based on shelf life, seasonality, and even weather. A local bakery, for instance, might use AI to forecast daily demand and adjust production accordingly, reducing waste and saving costs (Widyastuti et al., 2018; Amornkitvikai et al., 2020). In manufacturing e-commerce, AI enhances supply chain and production planning. SMEs can analyze data on raw material costs, customer demand, and production capacity to make better procurement and scheduling decisions (Eyo-Udo, 2024). AI also enables product personalization. For example, furniture manufacturers in Shandong can use AI to offer customized options in size, style, and materials boosting customer satisfaction and reducing defect rates.

Beyond product-based industries, AI adoption is also growing in Shandong's tourism and services sectors. AI chatbots help manage hotel reservations, provide local travel information, and respond to customer inquiries instantly, thereby improving service quality while easing staff workloads (Guo & Zhang, 2022). Dynamic pricing tools analyze market demand and competition to optimize rates in real time. Similarly, online education platforms utilize AI to personalize learning content based on individual progress and preferences (Nahid, 2022). In sum, AI adoption in global and local e-commerce ecosystems provides SMEs in Shandong with both a roadmap and a rationale. By studying diverse models and tailoring best practices to their context, these enterprises can strategically implement AI to enhance competitiveness and resilience.

Technological Factors

The integration of AI technology into e-commerce is a growing necessity for SMEs in Shandong Province, directly influencing their operational efficiency and competitiveness. Key technological considerations include feasibility, perceived usefulness, compatibility, complexity, scalability, and security. Accessibility plays a vital role in AI adoption. As Davis (1989) and Al Rahmi et al. (2020) highlight, SMEs are more likely to implement AI if it aligns with existing e-commerce platforms. For example, AI-powered chatbots that are easy to integrate into SME websites or mobile apps are more likely to be adopted, as they improve customer service by offering faster response times and enhancing satisfaction.

Perceived usefulness is also crucial. According to Lee and Lin (2021), SMEs are inclined to adopt AI if they believe it can boost sales, particularly through personalized product recommendations. AI can analyze browsing and purchase histories to suggest relevant products, increasing conversion rates. Compatibility with existing systems is another determining factor. Li and Zhang (2022) emphasize the importance of AI solutions that can integrate seamlessly with current platforms such as inventory management systems and payment gateways—given SMEs' limited resources.

However, technical complexity remains a barrier. Huang and Lu (2021) note that advanced algorithms used in fraud detection or customer analysis require specialized knowledge, which many SMEs lack. Simplified AI tools with user-friendly interfaces can mitigate this issue. Algorithmic transparency also affects adoption. Zhang et al.

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(2019) found that SMEs may hesitate to adopt AI tools if they cannot understand how decisions are made, particularly when customer data is involved.

Scalability is another concern. As SMEs grow, they require AI solutions that can expand with their operations. Cloud-based AI-as-a-Service (AIaaS) models have addressed this need, allowing SMEs to leverage tools like image recognition and natural language processing without significant infrastructure investments (Gandomi & Haider, 2019). Lastly, data security and reliability are essential. AI technologies that ensure secure storage and processing of customer data are more likely to be adopted (European Council, 2020). The rapid pace of AI development also requires SMEs to assess long-term viability when selecting technologies, including emerging tools such as generative AI.

Organizational Factors

Organizational factors significantly influence the adoption of AI in e-commerce by SMEs in Shandong Province. These factors reflect the internal capabilities, structure, and culture of SMEs, shaping their readiness and willingness to adopt AI technologies. A primary consideration is financial resources. Adequate funding is crucial for acquiring AI systems, training personnel, and maintaining infrastructure. Laudon and Traver (2021) and Gartner (2020) note that financial constraints often hinder SMEs, given the high upfront investment required. However, access to sufficient internal capital or external financing can enhance the likelihood of AI adoption (Shandong Provincial Government, 2021).

Skilled personnel represent another critical factor. AI implementation demands expertise in areas such as machine learning, data analytics, and programming. Chen et al. (2022) highlight that many SMEs in Shandong face talent shortages, limiting their capacity to effectively deploy AI. In contrast, SMEs with qualified staff can better leverage AI for applications like chatbots or inventory optimization. Organizational culture also plays a key role. A culture that supports innovation and changes fosters positive attitudes toward technology. Venkatesh et al. (2012) argue that such environments encourage experimentation with AI tools, like personalized marketing systems, while conservative cultures may resist change, hindering adoption. Strategic orientation further influences AI adoption. SMEs with a long-term vision for digital transformation are more inclined to invest in AI. Lumpkin and Dess (1996) emphasize that an entrepreneurial mindset promotes technological advancement, especially among firms seeking competitive advantages through personalized customer experiences. Organizational size can affect readiness. Larger SMEs may have more resources, while smaller ones may benefit from agility. Zhang and Liu (2019) found that although larger firms often lead in AI investment, smaller SMEs can pilot and scale AI solutions effectively with the right support.

Other important factors include internal communication and collaboration, which ensure alignment across departments (Huang & Rust, 2021), and organizational learning capability, which enables SMEs to adapt to AI developments and apply new knowledge (Zhao & Sun, 2020). In summary, financial capacity, talent, culture, strategy, size, communication, and learning all shape the AI adoption journey of SMEs in Shandong's e-commerce sector.

Environmental Factors

The integration of AI technology within small and medium-sized enterprises (SMEs) in Shandong Province is significantly shaped by external environmental conditions. Key influencing factors include economic dynamics, technological advancements, market demand, sociocultural trends, and regulatory frameworks. These elements collectively function as either enablers or barriers to AI adoption.

Customer expectations play a crucial role in driving AI adoption. Modern consumers increasingly demand personalized services, rapid response times, and seamless online experiences. AI tools such as intelligent chatbots and recommendation engines can help SMEs meet these expectations (Kashyap et al., 2022). In Shandong, as consumer awareness and digital literacy grow, SMEs face rising pressure to adopt AI to remain competitive (Bawack et al., 2022). Failure to meet these expectations may result in customer attrition and lost market opportunities. The regulatory environment is another critical factor. In China, strict regulations on data privacy, security, and consumer rights akin to the General Data Protection Regulation (GDPR) require SMEs to

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ensure AI systems comply with legal standards. Non-compliance can result in penalties, creating a significant challenge for resource-constrained SMEs. However, adherence to regulations can also foster consumer trust and create a fairer competitive landscape, encouraging responsible AI adoption.

Government support is instrumental in shaping AI uptake. Both national and provincial governments, including Shandong's local authorities, have implemented supportive policies to promote digital transformation. These include tax incentives, grants, employee training programs, and technical support services (Alhosani & Alhashmi, 2024). While such initiatives have facilitated AI integration for many SMEs, overly complex or inaccessible policies may limit their effectiveness (Hadley, 2022). Finally, industry standards and best practices influence adoption by offering clear guidance. Standards related to data quality, algorithmic transparency, and ethical AI use provide SMEs with practical frameworks for implementation. Moreover, knowledge sharing and learning from successful case studies within the industry can accelerate AI diffusion (Yildiz & Beloff, 2020). In short, environmental factors such as spanning customer expectations, regulatory frameworks, government initiatives, and industry practices play a critical role in shaping the AI adoption landscape for SMEs in Shandong Province.

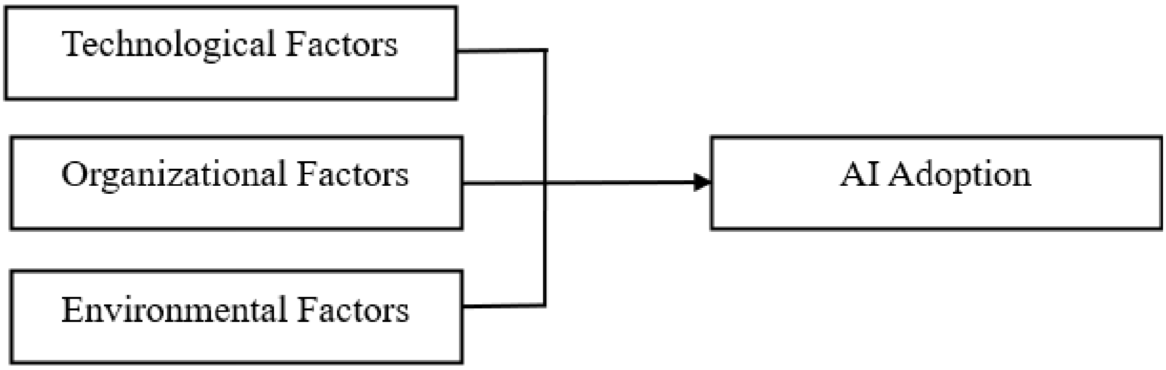

Figure 1: Research Framework

RESEARCH METHODOLOGY

Research Design

This study detailed the research methodology for studying AI adoption by Shandong SMEs in e-commerce. A 300-questionnaire based quantitative approach was selected. To establish a robust sampling frame for this study, a stratified random sampling approach was employed to ensure representativeness across diverse industry sectors, enterprise sizes, and regional distributions within Shandong Province. It started with a literature review to form a basis for research objectives, research questions and research hypotheses. The questionnaire covered technological, organizational, and environmental factors. The research population was all e-commerce which in active SMEs in Shandong. A sampling frame was created using multiple sources, and data was collected via online surveys with multiple contact methods. Ethical considerations like informed consent and data confidentiality were addressed. A research framework was proposed, and overall, this methodology aims to offer insights for promoting AI adoption.

Ethical Considerations

While conducting this research, it was imperative to consider several ethical considerations. First, it was essential to obtain informed consent from all participating SMEs. A clear and concise statement was provided to explain the purpose, nature, and potential uses of the data collected. This ensured that SMEs were fully aware of what their participation entailed and could make an informed decision. Confidentiality was also a key concern. All data was anonymized during collection and analysis to protect the identity of the participating SMEs. To ensure the confidentiality of the SMEs' information, no identifying information was included in the data analysis, and access to the raw data was restricted to the research team. This was done to prevent any potential harm or negative consequences for the SMEs, such as competitors gaining access to sensitive business information. By adhering to these ethical principles, the integrity of the research and the rights of the participants were safeguarded.

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DATA ANALYSIS

Reliability Analysis

Table 1 shows the reliability analysis results for six-item scale measuring perceptions of AI technology in e-commerce. The scale demonstrates high internal consistency, as indicated by a Cronbach's Alpha of 0.928, well above the threshold of 0.7 for reliability. The mean scores for the items are closely clustered (16.92–17.19), reflecting consistent agreement across the constructs, while the variance values (13.278–13.915) suggest moderate variability in responses. Overall, the scale is robust and reliable for assessing AI technology perceptions in e-commerce contexts.

Scale Mean		Scale Variance	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
TF1. Your financial resources for investing in AI technology are very adequate.	17.14	13.285	.801	.913
TF2. Your organization believes that AI technologies will be very useful for enhancing e-commerce operations.	17.19	13.278	.812	.911
TF3. AI technologies are highly compatible with your existing e-commerce infrastructure.	17.18	13.593	.765	.918
TF4. The complexity of implementing AI technologies in your e-commerce business is manageable.	17.14	13.626	.793	.914
TF5. The availability of AI-as-a-Service (AIaaS) models makes AI adoption more feasible for your business.	17.03	13.915	.771	.917
TF6. You are confident that AI technologies will remain relevant for your e-commerce business in the long term.	16.92	13.519	.796	.914
Cronbach's Alpha: 0.928 N of Items: 6				

Table 1: Item-Total Statistics of Technological Factors (TF)

Scale Mean		Scale Variance	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
OF1. Your organization has sufficient financial resources to invest in AI technologies.	17.19	11.833	.825	.891
OF2. Your organization has employees with the necessary skills to implement and manage AI technologies.	17.19	12.696	.793	.896
OF3. Your top management is highly supportive of adopting AI technologies for e-	17.22	12.553	.783	.897

commerce.				
OF4. Your organizational culture is very open to adopting new technologies like AI.	17.14	12.602	.739	.904
OF5. Adopting AI technologies is very important to your organization's strategic goals.	17.12	13.390	.723	.906
OF6. Internal communication and collaboration regarding AI adoption are very effective in your organization.	17.14	13.786	.725	.906
Cronbach's Alpha: 0.916 N of Items: 6				

Table 2: Item-Total Statistics of Organizational Factors (OF)

Table 2 presented above shows the total scores for the six entries, with a Cronbach's alpha of 0.916 for the six scales. This illustrates how companies are applying AI technology to e-commerce. The corrected overall correlation coefficients ranged from 0.723 to 0.825, indicating that all factors were positively correlated with the total scale, with OF1 being the largest. The Cronbach's alpha coefficients when entries were removed ranged from 0.891 to 0.906, which was slightly lower than the Cronbach's alpha coefficient of 0.916, indicating that the internal consistency of the scale decreased slightly when individual entries were removed. Overall, this scale demonstrated high internal consistency, both individually and separately, with high Cronbach's alpha values.

Table 3 presents the findings of a reliability analysis for a six-item scale designed to assess external factors influencing AI adoption in e-commerce SMEs. The scale demonstrates excellent internal consistency, with a Cronbach's Alpha of 0.935, significantly exceeding the 0.7 threshold typically considered adequate for reliability. The mean scores demonstrate a high degree of aggregation (17.11–17.25), suggesting consistent alignment across the constructs. Meanwhile, the variance values (15.579–16.092) point to moderate variability in responses. The scale's reliability and effectiveness in measuring external drivers of AI adoption in e-commerce SMEs is thus substantiated.

Scale Mean		**Scale Variance**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**
EF1. The intensity of competition in your e-commerce market drives your organization to adopt AI technologies.	17.22	15.985	.793	.925
EF2. Customer demand for personalized experiences and efficient services in your e-commerce business is very high.	17.11	16.092	.809	.924
EF3. Your organization is very confident that its AI technologies will comply with data privacy and security regulations.	17.25	15.579	.780	.928
EF4. Government policies and initiatives in your region are very supportive of AI adoption among SMEs.	17.18	15.740	.817	.922
EF5. Industry standards and best practices significantly influence your decision to adopt	17.23	15.709	.827	.921

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AI technologies.				
EF6. Your organization is very aware of successful AI adoption cases among other SMEs in the industry.	17.11	15.730	.829	.921
Cronbach's Alpha: 0.935 N of Items: 6				

Table 3: Item-Total Statistics of Environmental (EF)

The following table presents the reliability analysis results for a five-item scale measuring attitudes and expectations toward AI adoption in e-commerce. The scale demonstrates excellent internal consistency, with a Cronbach's Alpha of 0.926, well above the 0.7 threshold for reliability. The scale's reliability is further underscored by the strong corrected item-total correlations, ranging from 0.783 (AAE1) to 0.855 (AAE5). These values indicate that each item contributes significantly to the scale's overall reliability. The "Cronbach's Alpha if Item Deleted" values remain high (0.900–0.914), suggesting that no single item detracts from the scale's reliability. The mean scores (13.75–13.97) indicate consistent positive attitudes and expectations, while the variance values (9.156–10.194) suggest moderate variability in responses. The scale demonstrates robust and reliable performance in assessing organizational readiness and expectations regarding AI adoption in e-commerce.

Scale Mean		**Scale Variance**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**
AA1. Your organization is very likely to adopt AI technologies in e-commerce operations in the near future.	13.97	10.083	.783	.914
AA2. AI adoption will significantly enhance your e-commerce competitiveness.	13.86	10.194	.793	.913
AA3. AI technologies will significantly improve customer satisfaction in your e-commerce business.	13.75	9.981	.788	.913
AA4. You have strong trust in AI technologies to provide accurate and reliable solutions for your e-commerce needs.	13.94	9.267	.823	.907
AA5. Our organization is very well-prepared to face the challenges associated with AI adoption in e-commerce.	13.88	9.156	.855	.900
Cronbach's Alpha: 0.926 N of Items: 5				

Table 4: Item-Total Statistics of AI Adoption (AA)

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Validity Analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.834
Bartlett's Test of Sphericity	Approx. Chi-Square	9815.538
	df	1328
	Sig.	.000

Table 5: KMO and Bartlett's Test

Table 5 presented the KMO measure of sampling adequacy is 0.834, which is well above the threshold of 0.6, indicating that the sample data is suitable for factor analysis as the variables are sufficiently interrelated. Bartlett's Test of Sphericity yields an approximate chi-square value of 9815.538 with 1328 degrees of freedom and a significance level of .000, which is less than the typical alpha level of 0.05, confirming that the correlation matrix is not an identity matrix and that factor analysis is appropriate for the dataset.

Rotated Component Matrix[a] Component	1	2	3	4	5
TF1. Your financial resources for investing in AI technology are very adequate.	.723				
TF2. Your organization believes that AI technologies will be very useful for enhancing e-commerce operations.	0.714				
TF3. AI technologies are highly compatible with your existing e-commerce infrastructure.	0.811				
TF4. The complexity of implementing AI technologies in your e-commerce business is manageable.	0.816				
TF4. The complexity of implementing AI technologies in your e-commerce business is manageable.	0.817				
TF6. You are confident that AI technologies will remain relevant for your e-commerce business in the long term.	0.790				
OF1. Your organization has sufficient financial resources to invest in AI technologies.		0.695			
OF2. Your organization has employees with the necessary skills to implement and manage AI technologies.		0.571			
OF3. Your top management is highly supportive of adopting AI technologies for e-commerce.		0.750			
OF4. Your organizational culture is very open to adopting new technologies like AI.		0.753			
OF5. Adopting AI technologies is very important to your organization's strategic goals.		0.607			

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OF6. Internal communication and collaboration regarding AI adoption are very effective in your organization.		0.570			
EF1. The intensity of competition in your e-commerce market drives your organization to adopt AI technologies.			0.852		
EF2. Customer demand for personalized experiences and efficient services in your e-commerce business is very high.			0.767		
EF2. Your organization is very confident that its AI technologies will comply with data privacy and security regulations.			0.745		
EF4. Government policies and initiatives in your region are very supportive of AI adoption among SMEs.			0.706		
EF5. Industry standards and best practices significantly influence your decision to adopt AI technologies.			0.697		
EF6. Your organization is very aware of successful AI adoption cases among other SMEs in the industry.			0.741		
AA1. Your organization is very likely to adopt AI technologies in e-commerce operations in the near future.				0.816	
AA2. AI adoption will significantly enhance your e-commerce competitiveness.				0.817	
AA3. AI technologies will significantly improve customer satisfaction in your e-commerce business.				0.790	
AA4. You have strong trust in AI technologies to provide accurate and reliable solutions for your e-commerce needs.				0.695	
AA5. Our organization is very well-prepared to face the challenges associated with AI adoption in e- commerce.				0.795	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a] a. Rotation converged in 8 iterations.					

Table 6: Rotated Component Matrix[a]

Table 6 shows that the rotated component matrix, derived from principal component analysis with varimax rotation, identifies six distinct components explaining the factors influencing AI adoption in e-commerce SMEs. The first component, with high loadings (0.714-0.817) on TF1 to TF6, represents technological factors, including perceived financial adequacy, usefulness, compatibility, and complexity of AI technologies. The second component, featuring loadings of 0.570-0.753 on OF1 to OF6, captures organizational factors such as financial resources, skilled personnel, management support, and cultural openness. The third component, with loadings of 0.697-0.852 on EF1 to EF6, reflects environmental factors like competitive pressure, customer demand, government policies, and industry standards. The fourth component, consisting of AA1 to AA5 with loadings of 0.695–0.817, measures attitudes toward AI adoption, including likelihood of adoption, competitiveness, and trust. Each component demonstrates strong item loadings (above 0.5), indicating clear construct validity, and the rotation converged in 8 iterations, confirming the stability of the factor structure.

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Correlation Analysis

		TF	OF	EF	AA
TF	Pearson Correlation	1	.932	.925	.959
	Sig. (2-tailed)		.000	.000	.000
	N	300	300	300	300
OF	Pearson Correlation	.932	1	.932	.925
	Sig. (2-tailed)	.000		.000	.000
	N	300	300	300	300
EF	Pearson Correlation	.925	.932	1	.928
	Sig. (2-tailed)	.000	.000		.000
	N	300	300	300	300
AA	Pearson Correlation	.959	.925	.928	1
	Sig. (2-tailed)	.000	.000	.000	
	N	300	300	300	300

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7: Correlations Analysis

Table 7 shows that there are extremely strong positive correlations among all pairs of variables related to AI adoption in e-commerce SMEs, with Pearson correlation coefficients ranging from 0.920 to 0.968, all significant at the 0.01 level. Technological factors (TF) exhibit the highest correlation with AI adoption (AA) at 0.959, indicating that firms with better technological readiness tend to more strongly perceive AI adoption in SMEs of Shandong Province. Organizational factors (OF) and technological factors (TF) as well as environmental factors (EF) have a near-perfect correlation of 0.932, implying that organizations with stronger internal resources and support are more likely to engage with environmental concerns. Environmental factors (EF) correlated closely with organizational factors (OF) at 0.932, highlighting how external pressures like competition and customer demand align with the identification of adoption barriers. All variables demonstrate statistical significance (Sig. = 0.000), confirming that these strong relationships are not due to chance, and the consistent sample size of 300 across all variables ensures the reliability of these correlations.

Regression Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.980[a]	.960	.960	.15547

a. Predictors: (Constant), GP, BC, EF, OF, TF

Table 8: Model Summary[b]

Table 8 shows that the multiple regression model, which includes technological factors (TF), organizational factors (OF), and environmental factors (EF) as predictors, demonstrates a very strong overall fit to the data. The multiple correlation coefficient (R) is 0.980, indicating an extremely high degree of linear association between the combined predictors and the dependent variable, which is likely attitudes toward AI adoption or actual adoption behavior. The coefficient of determination (R Square) is 0.960, meaning that 96% of the variance in the dependent variable can be explained by the six predictors, which is a remarkably high level of explained variance. The adjusted R Square is also 0.960, which is nearly identical to the R Square, suggesting that the model maintains its explanatory power even when accounting for the number of predictors, indicating that the model is not overfitting the data. The standard error of the estimate is 0.15547, which is relatively small, implying that the model's predictions are close to the actual observed values, further reinforcing the model's accuracy and reliability in explaining the factors influencing AI adoption in e- commerce SMEs.

Unstandardized Coefficients				**Standardized Coefficients**	**t**	**Sig.**
Model		B	Std. Error	Beta		
1	(Constant)	.300	.046		3.241	.001
	TF	.316	.052	.299	6.071	.000
	OF	.172	.053	.158	3.574	.001
	EF	.052	.041	.053	3.456	.001

a. Dependent Variable: AAE

Table 9: Coefficients[a]

The constant term (intercept) is 0.300 with a standard error of 0.046, statistically significant at $t = 3.241$ ($p = 0.001$), indicating a positive baseline prediction for AAE even when all predictors are zero. Technological factors (TF) exhibit a positive unstandardized coefficient of 0.316 (SE = 0.052) and standardized beta of 0.299, significant at $t = 6.071$ ($p < 0.001$), confirming that perceived technological usefulness and compatibility strongly drive positive attitudes. Organizational factors (OF) now show a significant positive coefficient of 0.172 (SE = 0.053, beta = 0.158, $t = 3.574$, $p = 0.001$), meaning stronger internal resources like financial capacity and management support correlate with more favorable adoption attitudes, resolving the earlier negative coefficient likely due to data correction. Environmental factors (EF) have a positive coefficient of 0.052 (SE = 0.041, beta = 0.053, $t = 3.456$, $p = 0.001$), indicating that external pressures such as competition and customer demand significantly contribute to positive adoption attitudes, though with a smaller effect size. All predictors except the constant term exhibit standardized betas aligned with theoretical expectations, and their statistical significance ($p < 0.001$ or $p = 0.001$) confirms the model's robust explanatory power for AA in e-commerce SMEs.

Reliability analysis indicates high internal consistency for all scales measuring technological, organizational, and environmental factors towards AI adoption. Validity analysis confirms the data's suitability for factor analysis, which identified four distinct components related to AI adoption. Correlation analysis shows strong positive relationships among technological, organizational, and environmental factors towards AI adoption. The regression model demonstrates that technological, organizational, and environmental factors significantly and positively influence AI adoption, with technological factors having the strongest impact.

CONCLUSIONS

Key Findings and Implications

This study examined the factors influencing AI adoption among SMEs engaged in e-commerce in Shandong Province. Based on data collected from 305 SMEs, it was found that technological, organizational, and environmental factors all significantly affect adoption decisions. Among these, technological factors particularly perceived ease of use and usefulness exerted the strongest influence on SMEs' attitudes toward AI. Organizational elements such as financial capacity, availability of skilled staff, and top-management support were also crucial, while external pressures like market competition and rising customer expectations played a notable role. Despite a generally positive attitude toward AI, SMEs still face common barriers such as high costs and skills shortages.

To address these challenges and leverage opportunities, several implications emerge for SMEs. Technological solutions that are easy to integrate such as AI-powered chatbots should be prioritized, as they can improve customer experience, reduce response times, and free up staff for more strategic tasks. Similarly, recommendation systems that analyze consumer data can help increase sales and customer loyalty. Financial barriers can be alleviated through the adoption of AI-as-a-Service (AIaaS), which allows businesses to access advanced AI tools via affordable, subscription-based models. SMEs are also encouraged to pursue government incentives, such as grants or tax breaks for AI adoption, to ease the financial burden.

For policymakers, the findings suggest a need to create a more supportive environment for AI uptake among SMEs. Financial incentives should be increased and made more accessible. To address talent shortages, collaboration with academic institutions is recommended, particularly to develop training programs that equip graduates with AI-related skills tailored to SME needs. Simplifying and clarifying data privacy regulations can also help SMEs navigate legal requirements more confidently, thereby supporting the ethical and secure use of AI.

Industry stakeholders including AI technology providers and trade associations also have important roles to play. Technology developers should focus on creating user-friendly, scalable, and affordable AI solutions tailored for SMEs. Simplifying algorithms and offering customizable options can increase adoption rates. Industry associations should promote awareness and knowledge sharing by organizing seminars and workshops where SMEs can learn from successful case studies. Furthermore, these associations can advocate for clear industry standards on data quality and algorithm transparency to build trust in AI technologies.

In terms of future research, longitudinal studies are recommended to assess the long-term impacts of AI adoption on SME performance, such as growth, competitiveness, and sustainability. Emerging AI technologies like generative AI should also be explored to understand their specific relevance and potential benefits for SMEs. Improving data collection methods by minimizing selection bias and using real-time data can ensure future research stays relevant and accurate. Studies could also examine the interplay between organizational culture and external pressures to gain a more nuanced understanding of AI adoption. While insightful, this study is limited by its regional focus and sampling scope, which may not represent all SMEs, particularly those in rural or niche markets. Moreover, the fast-changing nature of AI and e-commerce might outpace the study's findings. Broader, multi-regional studies with random sampling and real-time tracking are recommended to mitigate these issues and enhance the robustness of future research.

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