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Analysis of Factors Influencing the Integration of Artificial Intelligence in Small and Medium-Sized Enterprises in Namangan Region

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Abstract: The main objective of this study was to identify effective approaches for implementing artificial intelligence (AI) technologies in small and medium-sized enterprises (SMEs) operating in the Namangan region. The findings reveal that top management commitment and organizational readiness exert the strongest influence on AI adoption, whereas employee adaptability, external support, and competitive pressure do not show a statistically significant impact. Data were collected from 196 business owners and managers through a Google Forms survey and analyzed using SmartPLS 4. The results enabled the identification of priority areas and practical recommendations for effective AI integration. Additionally, the study outlines future directions for enhancing AI implementation among SMEs in Namangan region.
Keywords: Artificial Intelligence (AI), Small and Medium-sized Enterprises (SMEs), Competitive Pressure, Employee Adaptability, Digitalization, Transformation

INTRODUCTION

In recent years, artificial intelligence (AI) technologies have been fundamentally transforming the activities of small and medium-sized enterprises (SMEs). Initially adopted by firms in developed countries, AI is now increasingly being applied across various sectors in Uzbekistan—from manufacturing to services—creating new competitive advantages for SMEs. Research demonstrates that AI can significantly strengthen the competitiveness of small businesses by reducing operational costs, improving customer interaction efficiency, and automating decision-making processes.

Uzbekistan, particularly the Namangan region, has been pursuing policies aimed at digitalization and entrepreneurship modernization, thereby enhancing the economic contribution of SMEs. As of October 1, 2025, approximately 68 percent of enterprises in the region are classified as SMEs, with 21.6 thousand small enterprises and microfirms operating. Despite this, the practical level of AI adoption remains very low, and challenges such as employee readiness, managerial trust in technology, and the availability of external support continue to be major barriers.

Global research indicates that AI is not merely a technological innovation; rather, it requires careful planning, sufficient investment, qualified professionals, and comprehensive training programs (Davenport et al., 2020; OECD, 2021). For SMEs, successful AI adoption involves identifying organizational needs, preparing employees to work with new systems, and ensuring the availability of high-quality data.

In Namangan, the main factors influencing AI adoption among enterprises include top management commitment (TMC), competitive pressure (CP), employees' digital skills and adaptability (EA), external support (ES), and the technical and organizational readiness (OR) of firms. These factors have not yet been studied in depth, and even large enterprises in the region have not fully addressed them. This reveals a clear scientific gap and underscores the relevance of the present study.

Moreover, SMEs in the region operate in services, agriculture, light industry, and other sectors, playing an essential role in the area's economic and social development. Therefore, identifying, systematizing, and assessing the sector-specific characteristics of AI adoption is crucial for developing effective scientific and practical solutions.

LITERATURE REVIEW

In recent years, the integration of artificial intelligence (AI) into small and medium-sized enterprises (SMEs) has emerged as one of the central research themes within the global scientific community. In academic literature, Artificial intelligence (AI) refers to the field of computer science that focuses on creating intelligent machines capable of performing tasks that typically require human intelligence (Joiner, 2018). AI systems are designed to analyze and interpret data, learn from experiences, make decisions, and solve problems like human cognition. They rely on algorithms, machine learning techniques, and large datasets to acquire knowledge, improve performance, and adapt to changing circumstances (Xu et al., 2021). AI encompasses various subfields, including natural language processing, computer vision, robotics, expert systems, and neural networks, and it finds applications in diverse domains such as healthcare, finance, transportation, gaming, SMEs, and marketing strategy (Baabdullah et al., 2021; Ma and Sun, 2020; Mikalef et al., 2023; Moradi and Dass, 2022; Rosa et al., 2021; Thayyib et al., 2023). There are several ways in which small and medium-sized enterprises (SMEs) may benefit from the use of artificial intelligence technology, including the chance to streamline internal processes (Bettoni et al., 2021), make better decisions (Ragazou et al., 2023), and boost productivity (Wu et al., 2023). Several earlier studies, however, have discussed the limitations and constraints in the application of AI among SME participants (Hansen and Bøgh, 2021; Moradi and Dass, 2022; Ulrich and Frank, 2021). As a result, the dialog concerning AI and SMEs expands.

Competitive pressure (CP) refers to the influence and intensity of competition faced by businesses in a particular market or industry. It encompasses the factors that drive companies to continuously improve their products, services, and strategies to gain a competitive advantage (Baabdullah et al., 2021). CP arises from various sources, such as the presence of rival firms, customer demands, technological advancements, pricing dynamics, and regulatory conditions. Businesses must navigate and respond to competitive pressure effectively to sustain and thrive in the marketplace (Wu et al., 2023). AI enables competitive analysis, personalized marketing, pricing optimization, customer experience enhancement, and predictive analytics. It helps businesses gain insights, target customers effectively, optimize pricing strategies, enhance customer experiences, and make data-driven decisions to stay competitive. A significant number of empirical investigations found that higher levels of innovative adoption are associated with higher levels of competitive pressure (McDougall et al., 2022; Sin et al., 2016; Tajeddini et al., 2023; Wu et al., 2023). This pressure also pushes SMEs to incorporate AI into their day-to-day operations. Based on the above discussion, CP compels businesses to utilize AI technology in their marketing strategies (Gonçalves et al., 2022), therefore the following hypothesis is proposed:

H1.: *Competitive Pressure (CP) pushes SMEs significantly for AI adaptation.*

Top management commitment (TMC) refers to the level of support and dedication demonstrated by the top management of an organization towards a particular initiative or decision (Daoud et al., 2021). In the context of SMEs (small and medium-sized enterprises), TMC plays a crucial role in strategic decision-making. Strategic decisions in SMEs involve important choices that shape the long-term direction and competitive position of the business (Dubey et al., 2018; Soltani, 2005). These decisions can include selecting target markets, developing new products or services, entering into partnerships or alliances, adopting new technologies, or exploring international expansion, among others. TMC plays a critical role in the context of SMEs when it comes to strategic decision-making related to the adoption and implementation of artificial intelligence (AI) technologies (Deepu and Ravi, 2021; Jayashree et al., 2021). Previous studies have proven that there is a clear relationship between TMC and AI adoption. This is because TMC is essential in SME strategic decision-making regarding AI adoption. It drives the recognition of AI's potential, supports its integration, overcomes resistance to change, and ensures the realization of AI benefits (Lemos et al., 2022; Rosa et al., 2021). TMC plays a crucial role in leveraging AI as a strategic tool to enhance the decision-making, competitiveness, and overall performance of SMEs. Following the findings above, the following hypothesis will be tested.

H2.: *SME's Top Management Commitment (TMC) significantly influences AI adaptation.*

Employee Adaptability (EA) refers to an individual's ability to adjust and thrive in changing work environments. It involves being flexible, open-minded, and quick to learn and adapt to new technologies, processes, and roles (Murphy, 2016; van Dam, 2009). In the context of SMEs, EA becomes crucial as these businesses often operate in dynamic and competitive markets that require constant adaptation to stay relevant. The relationship between Employee Adaptability and AI in SMEs is significant (Drydakis, 2022). AI technologies, such as automation, machine learning, and data analytics, are increasingly being implemented in various business functions. These technologies can streamline processes, improve productivity, and enhance decision-making. However, they also require employees to possess adaptability skills to effectively utilize and integrate AI into their work (Ganlin et al., 2021). SME employees with strong adaptability skills can quickly learn how to leverage AI tools, adapt their job roles to work alongside AI systems and acquire new skills as required. They can embrace the changes brought by AI, embrace the opportunities it presents, and contribute to the successful implementation and utilization of AI technologies within their organization. Overall, EA plays a vital role in enabling SMEs to effectively adopt and integrate AI into their operations, ultimately driving innovation, competitiveness, and growth in today's rapidly changing business landscape. The following hypothesis is based on the fact that staff adaptability and effective AI integration are mutually dependent.

H3.: *Employee adaptability significantly influences the adoption of AI technologies.*

External support (ES) plays a vital role in facilitating AI adoption for SMEs in their business operations. This is because SMEs often lack the necessary expertize, resources, and infrastructure to fully leverage the potential of AI technology (Maroufkhani et al., 2020). ES in AI adoption for SMEs encompasses expertize, technical assistance, customization, data management, training, and continuous support. These services enable SMEs to harness the benefits of AI technology, optimize their operations, and remain competitive in an increasingly digital business landscape (Drydakis, 2022). By leveraging ES, SMEs can overcome challenges related to AI implementation and enhance their overall performance in the following ways; improved efficiency, enhanced decision-making, competitive advantage, and better customer service (Gonçalves et al., 2022; Ragazou et al., 2023; Sjödin et al., 2021).

Therefore, the relationship between external support in AI adoption and SMEs' business performance is symbiotic. ES enables SMEs to overcome AI implementation challenges, leverage the power of AI technologies, and achieve improved efficiency, better decision-making, competitive advantage, enhanced customer service, data-driven insights, and scalability (Fountaine et al., 2019; OECD, 2021). These factors collectively contribute to enhancing SMEs' overall business performance. Based on the above literature, we proposed the following hypothesis:

***H4.:** External support (ES) significantly influences the adoption of AI technologies*

Organization readiness (OR) in AI adoption has a significant impact on SMEs' operations and performance. OR refers to the preparedness of an organization, including its leadership, employees, culture, infrastructure, and processes, to effectively adopt and leverage AI technologies (Hradecky et al., 2022). However, before implementing the changes within the organization, preparedness for change is crucial (Hashim et al., 2021). Additionally, careful and ongoing planning in change management is necessary for the introduction of new technology to ensure the effective achievement of the technology's goal (Jalagat, 2016). Therefore, high OR aligns AI adoption with business strategy, enables effective change management, ensures robust data management capabilities, provides suitable technical infrastructure, fosters collaboration and skill development, and promotes a culture of continuous improvement (Aboelmaged, 2014; Hradecky et al., 2022). These factors collectively contribute to improved operational efficiency, enhanced decision-making, better utilization of resources, and ultimately, higher performance for SMEs.

Based on the above findings, OR in AI adoption significantly influences SMEs' operations and performance, therefore we proposed the following hypothesis:

***H5.:** Organization Readiness (OR) significantly influences the adoption of AI technologies.*

METHODOLOGY

This research aims to systematically and comprehensively examine the process of adopting artificial intelligence (AI) technologies among small and medium-sized enterprises (SMEs) operating in the Namangan region. The research model incorporates six key variables categorized into internal factors—Top Management Commitment (TMC), Organizational Readiness (OR), and Employee Adaptability (EA)—and external factors—Competitive Pressure (CP) and External Support (ES).

The hypotheses were developed based on existing theoretical models and previous studies (Daoud et al., 2021; Rosa et al., 2021), allowing the relationships among the variables to be empirically tested. The conceptual model of the study, presented in Figure 1, visually illustrates the main factors influencing AI adoption within the SME context of Namangan region and establishes the theoretical foundation of the research.

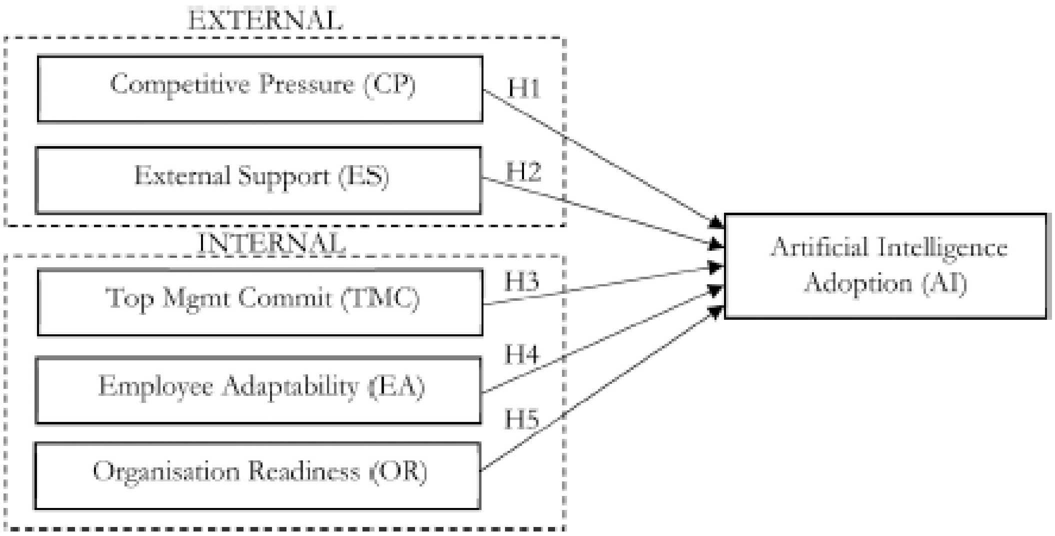

Figure 1. Conceptual framework of the research

The study examines six major constructs that influence AI adoption—Top Management Commitment (TMC), Organizational Readiness (OR), Employee Adaptability (EA), Competitive Pressure (CP), External Support (ES), and AI Adoption—forming the conceptual basis of the proposed model. Data were collected using a seven-point Likert scale, where 1 represented "strongly disagree" and 7 represented "strongly agree." The measurement items were adapted from Daoud et al. (2021) and Rosa et al. (2021), and subsequently assessed for face validity by two academics and two SME owners. Based on their feedback, a pilot study was conducted to enhance the clarity and reliability of the questionnaire.

The unit of analysis consisted of individual respondents—business owners or managerial-level executives—who were assumed to possess adequate knowledge regarding AI-related decision-making and implementation within their companies. Data were collected from owners and managers of SMEs operating in various sectors across Namangan region, including services, manufacturing, construction, agriculture, trade, and others. The sampling frame covered all registered small enterprises and micro-firms in the region. Questionnaires were distributed via email, Google Forms, and telephone after obtaining prior permission from company management. Data collection took place between January and September 2025.

The minimum sample size was calculated using the G*Power software, considering the presence of five predictors in the model, an effect size of 0.15, and a statistical power of 0.95. Accordingly, the minimum required sample was 138 respondents. During the study, a total of 300 questionnaires were distributed, and 196 valid responses were received (response rate: 65.3%), which exceeded the minimum requirement and was deemed sufficient.

A judgmental (purposive) sampling technique was employed to select respondents, ensuring coverage of diverse sectors and business sizes, and targeting individuals in managerial positions who actively participate in AI implementation within their organizations. The collected data were analyzed using SmartPLS 4, and the hypotheses were tested through a path model based on regression coefficients. SmartPLS 4 is appropriate for studies with relatively small sample sizes and supports the validation of prediction-oriented theoretical models (Hair et al., 2019).

Additionally, Harman's single-factor test was used to check for Common Method Bias (CMB). The first component accounted for 36.8% of the total variance, indicating that CMB did not significantly affect the results of the study and was therefore considered negligible.

ANALYSIS AND RESULTS

When analyzing the respondents' profile, the data reflect the distribution of small and medium-sized enterprises (SMEs) across different sectors. Table 1 presents the number of SMEs in each sector along with their corresponding percentage values. A total of 196 SMEs participated in this study, with each sector contributing to the overall percentage distribution. The highest concentration of SMEs operates in the services sector, comprising 65 enterprises, which accounts for 33.16% of all SMEs. This is followed by the manufacturing sector with 32 enterprises, representing 16.32% of the total. The construction sector includes 21 SMEs, making up 10.71% of the sample.

Additionally, 76 SMEs operate in the agriculture sector, representing 38.77% of the total. Finally, the mining and extraction sector has the smallest representation, with only 2 SMEs, accounting for 1.02%.

Table 1

Respondents' profile based on sector

SME sector	N (owner / manager)	%
Services	65	33.16
Manufacturing	32	16.32
Construction	21	10.71
Agriculture	76	38.77
Quarrying & Mining	2	1.02
Age		
18–25 years old	6	3.06
26–33 years old	29	14.79
34–41 years old	66	33.67
42–49 years old	53	27.04
50 years old and from it big	42	21.42
Gender		
Male	124	63.26
Female	72	36.73

In terms of age, the largest group of respondents falls within the 34–41-year-old category, consisting of 66 participants. This is followed by the 42–49-year-old group, which includes 53 respondents. The youngest age group, those aged 18–25, is the smallest, with only 6 participants.

With respect to gender, the majority of respondents are male, accounting for 124 individuals, while female respondents make up 72 individuals. The sectoral profile of the sample is reflective and representative of SMEs in the Namangan region (Local Statistics Department, 2025).

The validity of the measurement model refers to the extent to which the model accurately measures the designated construct or concept. This is particularly important in ensuring that the measurements used in the context of SMEs in the Namangan region are both reliable and meaningful. According to Hoyle (2011) and Kline (2010), a measurement model evaluates latent or composite variables. The validity of the measurement model is assessed using three criteria: construct validity, convergent validity, and discriminant validity (Ahmad et al., 2016; Hair et al., 2019).

To evaluate the convergent validity of the constructs, factor loadings, Composite Reliability (CR), Average Variance Extracted (AVE), and reliability (Cronbach's Alpha) were calculated (Fornell & Larcker, 1981). In this study, these metrics were assessed for SMEs in the Namangan region. Convergent validity is considered to be present when the following three conditions are met:

CR values are 0.7 or higher,

All standardized factor loadings are 0.5 or higher,

AVE values are 0.5 or higher (Cheung et al., 2023; Henseler et al., 2015).

Table 2

Construct validity and reliability

Construct	Code / elements	Loadings	AVE	CR	Cronbach Alpha
Artificial intellect adoption (AI)	AI1	0.992	0.980	0.995	0.993
	AI2	0.985			
	AI3	0.994			
	AI4	0.990			
Competitive pressure (CP)	CP1	0.879	0.771	0.931	0.903
	CP2	0.823			
	CP3	0.895			
	CP5	0.914			
Employees Adaptability (EA)	EA1	0.824	0.641	0.877	0.824
	EA2	0.872			
	EA3	0.802			
	EA4	0.696			
External support (ES)	ES2	0.960	0.710	0.894	0.880

Construct	Code / elements	Loadings	AVE	CR	Cronbach Alpha
	ES3	0.849			
	ES4	0.760			
Organization readiness (OR)	OR1	0.996	0.959	0.969	0.986
	OR2	0.964			
	OR3	0.973			
	OR4	0.982			
Top management Commitment (TMC)	TMC 1	0.875	0.961	0.990	0.986
	TMC 3	0.871			
	TMC 4	0.876			
	TMC 5	0.850			

According to the results presented in Table 2, the measurement model fully satisfies the requirements for construct reliability (CR), standardized loading, average variance extracted (AVE), and internal consistency reliability (Cronbach's Alpha). The CR values range from 0.877 to 0.995, indicating a high level of internal consistency and reliability within the measurement model. The high CR values confirm that the indicators reliably measure their corresponding latent constructs.

The standard loadings vary between 0.696 and 0.992, demonstrating strong associations between the indicators and their respective latent constructs. The AVE values range from 0.64 to 0.990, reflecting the extent to which the variance of the indicators is explained by the latent constructs. Higher AVE values indicate that a substantial proportion of indicator variance is captured by the constructs.

Cronbach's Alpha values range from 0.800 to 0.993, further confirming the internal consistency and reliability of the measurement items. Overall, the results show that the measurement model exhibits a high level of validity in the context of SMEs in the Namangan region.

Discriminant validity refers to the extent to which a construct is more strongly correlated with its own indicators than with indicators of other constructs (Hair et al., 2017; 2019). The Fornell–Larcker criterion, which is widely used to assess discriminant validity (Ab Hamid et al., 2017), requires that the square root of each construct's AVE should be greater than its correlations with other constructs.

Table 3

Discriminant Validity : Heterotrait – Monotrait ratio (HTMT)

Construct	AI	CP	EA	ES	OR	TMC
Artificial Intelligence (AI)	0.980					
Competitive Pressure (CP)	0.206	0.771				
Employees Adaptability (EA)	0.339	0.361	0.641			
External Support (ES)	0.078	0.504	0.219	0.710		
Organization Readiness (OR)	0.585	0.206	0.222	0.127	0.959	
Top Management Commitment (TMC)	0.508	0.556	0.511	0.112	0.392	0.961

The Heterotrait–Monotrait (HTMT) ratio was also employed, as it is considered a highly sensitive and accurate method for detecting discriminant validity issues (Henseler et al., 2015). According to the results in Table 3, all HTMT values fall below the threshold of 0.85, confirming that adequate discriminant validity exists among the constructs. The correlations between each construct and indicators of other constructs are lower than the correlations with their own indicators, demonstrating that the constructs are clearly distinguishable and not conceptually overlapping.

These results verify that the measurement model exhibits strong discriminant validity within the context of SMEs in the Namangan region.

In the PLS-SEM methodology, the structural model focuses on assessing the significance and relevance of path coefficients, which subsequently allows for the evaluation of the model's explanatory and predictive power. The structural model reflects the hypothesized relationships presented in the research framework. The significance of the paths is assessed together with the R^2 and Q^2 values, which collectively indicate the model's robustness.

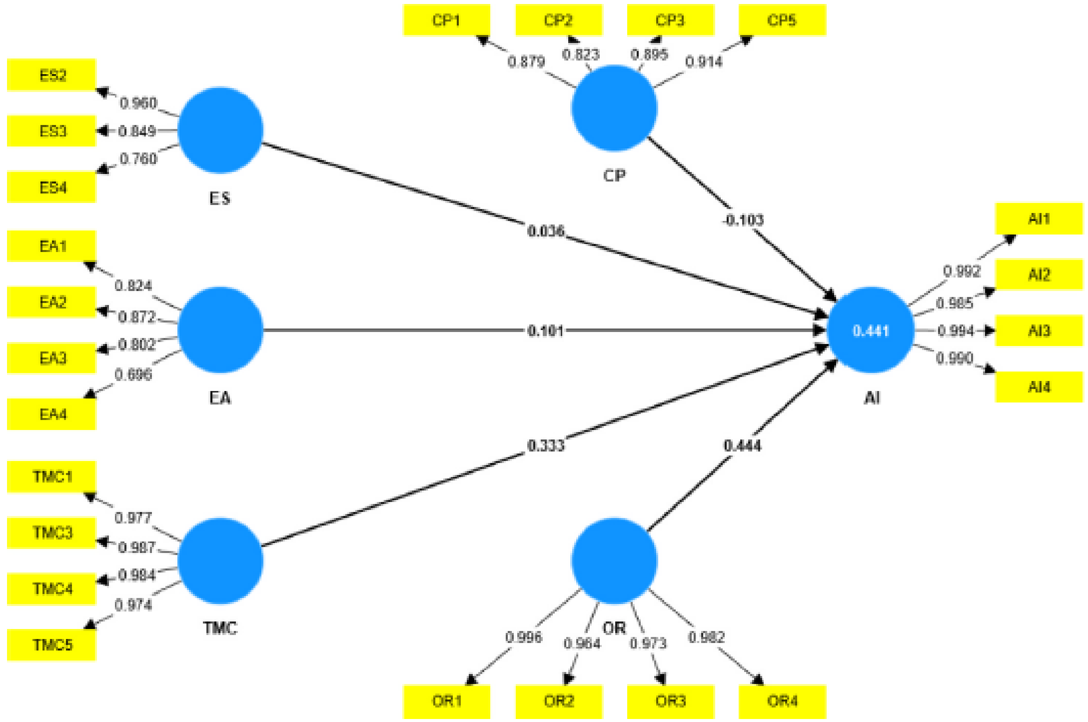

Figure 2. Structural model path coefficients

According to the results presented in Figure 2, the R^2 value of the model is 0.441, indicating that the independent variables collectively explain approximately 44.1% of the variance in AI adoption. In other words, the independent variables—CP, ES, EA, OR, and TMC—together account for 44.1% of the changes in AI adoption.

The overall quality of the model can be evaluated by examining the strength of each structural path. An R^2 value of 0.1 or higher is considered acceptable (Falk & Miller, 2014). As shown in Figure 2 and Table 4, the R^2 value of 0.441 exceeds this threshold, confirming the model's predictive power. The Q^2 value further supports the model's predictive relevance, with $Q^2 = 0.339$, indicating substantial predictive accuracy. Additionally, the SRMR value of 0.059 is below the recommended cutoff of 0.10, demonstrating that the model exhibits an acceptable level of fit (Hair et al., 2016).

The results indicate that Top Management Commitment (TMC) and Organizational Readiness (OR) have significant effects on AI adoption (OR → AI: $\beta = 0.444$, $t = 6.324$, $p < 0.001$; TMC → AI: $\beta = 0.333$, $t = 4.16$, $p < 0.001$). Therefore, hypotheses H2 and H5 are supported.

However, the variables CP, EA, and ES do not show significant effects on AI adoption, leading to the rejection of hypotheses H1, H3, and H4. Statistically, this implies that changes associated with TMC and OR have a meaningful influence on AI adoption outcomes. This suggests that SMEs can improve AI-related outcomes by strengthening practices related to TMC and OR.

Overall, these findings provide guidance for decision-making and resource allocation, highlighting the importance of OR and TMC in enhancing AI-related outcomes, while showing that some variables do not exert significant influence. These results differ slightly from the conclusions of previous research (Rosa et al., 2021), which did not identify significant effects of TMC and OR. Nonetheless, the findings are consistent with those of Daoud et al. (2021), who found the CP variable to be significant.

DISCUSSION

The research findings indicate that Top Management Commitment (TMC) and Organizational Readiness (OR) exert significant influence on the adoption of artificial intelligence (AI), thereby supporting hypotheses H2 and H5. The positive association between TMC, OR, and AI adoption suggests that SMEs can strategically plan investments aimed at improving AI-driven outcomes. This underscores the importance of TMC and OR in decision-making processes and resource allocation, while also highlighting sectors where the effectiveness of AI-related practices may be limited.

From a strategic perspective, the significant relationship between OR and AI demonstrates the necessity for organizations to enhance their level of preparedness (Aboelmaged, 2014). This process involves simplifying operational workflows, improving efficiency, and investing in technological upgrades. Similarly, the strong link between TMC and AI adoption emphasizes the need to prioritize the development of employees' technological and managerial competencies, ensuring that they possess the required capabilities to utilize AI technologies effectively.

However, in SMEs where top management commitment is insufficient, contradictory outcomes may arise (Furuholt & Ørvik, 2006). The findings indicate that the absence of TMC support results in lower levels of AI adaptation and integration. Thus, TMC is a crucial strategic factor in facilitating AI acceptance and successful implementation among SMEs (Daoud et al., 2021).

TMC contributes to successful AI adoption by defining the strategic direction and vision of the organization, allocating financial and human resources to AI initiatives, and ensuring that the necessary infrastructure is in place for AI integration (Dubey et al., 2018; Soltani, 2005; Deepu & Ravi, 2021; Lemos et al., 2022). Without strong support from TMC, coordinating the resources required for AI technologies and attracting qualified personnel becomes significantly more difficult.

Effective AI implementation requires firm commitment from top management. At the initial stage, leaders must be made aware of the potential benefits of AI and its alignment with organizational strategic goals. Demonstrating AI's contributions to efficiency, innovation, and growth through practical cases and examples can further reinforce its value. Additionally, ensuring that AI initiatives align with the organization's strategic objectives enables companies to recognize AI's potential in generating competitive advantage, increasing revenue, reducing costs, and enhancing customer experience. In the final stage, AI solution providers can assist organizations in developing a step-by-step implementation strategy, including timelines, key deliverables, and expected outcomes.

In summary, the findings highlight the crucial role of TMC and OR in AI adoption and emphasize the need for SMEs to strengthen strategic resource management, employee readiness, and technological investments. At the same time, the non-significant variables (CP, EA, ES) indicate the need for further research and contextual refinement in future studies.

CONCLUSION

This study aims to identify the key factors influencing the adoption of artificial intelligence (AI) technology among small and medium-sized enterprises (SMEs) in the Namangan region. Data were collected from 196 respondents using a judgemental sampling technique and analyzed through the PLS-SEM and bootstrapping methods in SmartPLS 4. The results confirmed the reliability and validity of both the measurement and structural models.

The analysis revealed that Top Management Commitment (TMC) and Organizational Readiness (OR) play a crucial role in AI adoption. Therefore, SMEs are advised to prioritize investments in these factors to strategically allocate resources and enhance AI-related outcomes. Although other factors—Competitive Pressure (CP), Employee Adaptation (EA), and External Support (ES)—show potential influence, they did not demonstrate a statistically significant impact on AI adoption.

These findings provide deeper insights into the opportunities and challenges associated with AI adoption among SMEs, enabling the development of more effective strategies, frameworks, and practical tools. Implementing AI technology can serve as a catalyst for improving competitiveness and fostering sustainable growth among SMEs in the Namangan region. However, organizations that have not sufficiently embraced AI may struggle with effective implementation, and overcoming related barriers is essential for broader and more successful AI adoption.

The limitations of this study include a relatively small sample size (196 respondents), which may restrict the generalizability of the findings. SMEs in different regions may experience unique opportunities and challenges in adopting AI due to variations in local regulations, market conditions, and resource availability. Additionally, the research is quantitative in nature and relies on respondents' perceptions, without incorporating direct observations of AI implementation processes.

Future research is recommended to:

Examine a larger and more diverse sample of SMEs across multiple regions.

Conduct an in-depth analysis of AI adoption within specific business processes such as product development, customer service, sales, and marketing.

Employ qualitative research designs or case-study methodologies to gain deeper insights into the factors and barriers affecting AI adoption.

These recommendations will help SMEs successfully implement AI technologies and utilize them with maximum efficiency.

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